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Projecting Future Costs to U.S. Electric Utility Customers from Power Interruptions

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Table of Contents

Table of Figures

List of Tables

Abstract

This analysis integrates regional models of power system reliability, output from atmosphere-ocean general circulation models, and results from the Interruption Cost Estimate (ICE) Calculator to project long-run costs to electric utility customers from power interruptions under different future severe weather and electricity system scenarios. We discuss the challenges when attempting to model long-run costs to utility customers including the use of imperfect metrics to measure severe weather. Despite these challenges, initial findings show that discounted cumulative customer costs, through the middle of the century, could range from $1.5-$3.4 trillion ($2015) without aggressive undergrounding of the power system and increased utility operations and maintenance (O&M) spending and $1.5-$2.5 trillion with aggressive undergrounding and increased spending. By the end of the century, cumulative customer costs could range from $1.9-$5.6 trillion (without aggressive undergrounding and increased spending) and $2.0-$3.6 trillion (with aggressive undergrounding and increased spending). We find that, in some scenarios, aggressive undergrounding of distribution lines and increased O&M spending is not always cost-effective. We conclude by identifying important topics for follow-on research, which have the potential to improve the cost estimates of this model.

1. Introduction

Government policies, the deployment of smart grid technologies, and an increase in catastrophic weather events have focused attention on the reliability of electric power systems in the United States (U.S.) and around the world (Larsen et al. 2015, Larsen et al. 2016). Adverse weather, equipment failure, human error, vegetation management practices, wildlife, and other, occasionally unknown factors have been documented as causes of power interruptions (Hines et al. 2009; Larsen 2016a). The U.S. Department of Energy (DOE) reports that adverse weather is the most common cause of power interruptions, and that the weather-related impacts to the power system have increased significantly over the past twenty years (U.S. DOE 2015). Melillo et al. (2014) found that some extreme weather "have increased in recent decades…extreme weather events and water shortages are already interrupting energy supply and impacts are expected to increase in the future". In addition to the potential for more frequent and extreme weather, aging power system infrastructure and an observed decrease in power system reliability highlight the importance of projecting the costs of future power interruptions to customers. Despite a general understanding that power system interruptions may increase in the future, long-term economic analyses for the U.S. have not been conducted. However, the need for such information could not be larger, particularly given the importance of power system reliability to the U.S. economy.

This analysis integrates regional models of power system reliability, projections from atmosphere-ocean general circulation models (AOGCMs), and results from the Interruption Cost Estimate (ICE) Calculator to estimate the potential economic implications of future reliability under different future severe weather and electricity system scenarios. This paper is organized as follows. We introduce the analysis method and data sources in section two. Section three contains the results and comments on the limitations of this modeling effort. Section four concludes by summarizing the findings and identifying some possible avenues for future research.

2. Analysis Method and Data Sources

Applied, engineering-economic research into power system reliability has traditionally focused on how historic power interruptions impact societal systems (e.g., see Ji et al. 2016; Ward 2013; Alvehag and Söder 2011; Hines et al. 2009). Ji et al. (2016) examined outages in New York State during Hurricane Sandy finding that "local power failures have a disproportionally large non-local impact on people…extreme weather exacerbates existing vulnerabilities which are obscured in daily [utility] operations". However, there has been little research conducted that evaluates past trends in reliability and no known national (U.S.) studies that project future power system reliability under alternative scenarios. Hines et al. (2009) evaluate past North American blackouts and discuss trends within the context of weather-related causes. Alvehag and Söder (2011) develop a reliability model which considers the historical impact of abnormally high wind speeds and lightning strikes on utilities operating in Sweden. Eto et al. (2012), Larsen et al. (2015; 2016), and Larsen (2016a) conducted research evaluating long-term trends in reliability performance data collected by electricity distribution companies. Eto et al. (2012) collected information on the annual average number of minutes and count of power interruptions for a cross-section of electricity distribution utilities across the U.S., and performed an econometric analysis to correlate annual changes in reliability with a set of explanatory variables, including basic measures of annual weather. Larsen et al. (2015; 2016) and Larsen (2016a) expanded on the Eto et al. (2012) methodology by including—among other things—measures of extreme weather (i.e., "abnormal weather"), utility spending on transmission and distribution (T&D) operations and maintenance (O&M), and undergrounding. In parallel, the Lawrence Berkeley National Laboratory (LBNL) and its partners developed and continue to maintain the Interruption Cost Estimate (ICE) Calculator which is "designed for electric reliability planners at utilities, government organizations or other entities that are interested in estimating interruption costs and/or the benefits associated with reliability improvements" (Sullivan et al. 2015)[1].

Projecting the frequency and costs to customers of power interruptions across the continental U.S. involves a number of important steps. First, an econometric model—based on the earlier research of Eto et al. (2012), Larsen et al. (2015; 2016) and Larsen (2016a)—was developed and calibrated with the intent of forecasting regional power system reliability decades into the future. To this end, a set of explanatory variables, including measures of abnormal weather; utility sales and O&M spending; share of underground line miles, etc., were projected and then included in the regional models of power system reliability in order to project the long-term frequency and average annual duration of power interruptions under various scenarios. The annual frequency and average duration of each power interruption—as well as the mix of customer types and other electricity system characteristics—were then used to estimate the future costs of power interruptions for electric utility customers located across the U.S. Finally, this integrated model was rerun to simulate the avoided interruption costs from increasing the percentage share of underground line miles and O&M spending—a strategy that has been linked to improved reliability (Larsen et al. 2015; Larsen et al. 2016; Larsen 2016a; Larsen 2016b). The primary stages of this method are described in the following sections.

A. Regional model of power system reliability

Equations (1) and (2), below, describe the reliability metrics (i.e., dependent variables) used in the national reliability model specified by Eto et al. (2012) and Larsen et al. (2015; 2016). In the following equations, *Time* represents the total amount of time in a given year, t, when customers are without power; *Affected* is the number of customers impacted by all power interruptions in a given year, t; and *Customers* are the total number of customers—regardless of whether they were impacted by an interruption or not—for the utility in a given year, t.

$$\mathrm{SAIDI}_t = \frac{\sum \mathrm{Time}_t \times \mathrm{Affected}_t}{\mathrm{Customers}_t}$$

(1)

[1] The ICE Calculator can be accessed at http://icecalculator.com/.

It follows that the System Average Interruption Duration Index (SAIDI) and the System Average Interruption Frequency Index (SAIFI) are annual measures of the total number of power interruption minutes and the frequency, respectively, which an average utility customer experiences over the course of a year.

$$\mathrm{SAIFI}_t = \frac{\sum \mathrm{Affected}_t}{\mathrm{Customers}_t} \tag{2}$$

The national reliability model described in Larsen et al. (2015; 2016) and Larsen (2016a) serves as the foundation of this integrated model to estimate the future costs of power interruptions across a number of U.S. regions. In this model, SAIDI and SAIFI are a function of a number of explanatory variables including utility characteristics, abnormal weather, and a time trend, which was shown to have strong statistical significance in earlier research (e.g., Larsen et al. 2015; 2016). The reliability model specification used in this analysis (see equation three) follows the general form used in earlier energy-related multivariate panel regressions (e.g., see Erdogdu 2011; Eto et al. 2012; Larsen et al. 2015; Larsen et al. 2016; Larsen 2016a).

$$\ln(Y_{it}) = \beta_0 + \beta_r + \sum_{j=1}^{n} B_j X_{jit} + \alpha_i + \delta T + \varepsilon_{it} \tag{3}$$

In this model of power system reliability, annual utility reliability (SAIDI or SAIFI) is represented by the dependent variable: Y_{it}, which is logged. Electric utility, utility region, and reporting year are represented by subscripts i, r, and t, respectively. X_{jit} represents an array of observed, explanatory variables (j) over time. For example, variables in X include, among other things, annual O&M expenditures on the transmission and distribution (T&D) system and abnormally high wind speeds. α_i represents the combined effect of electric utility-level, unobservable variables on the dependent variable, Y_{it}. Finally, ε_{it} represents the model error term and T is a variable to capture an annual time trend (Larsen et al. 2015).

The Larsen et al. (2015; 2016) Model F (fixed effects model) was re-run to produce utility-level effects with standard error terms corrected for both heteroscedasticity and autocorrelation[2]. Next, regionally-specified equations of power system reliability were developed in order to produce results that would

[2] Zeileis (2004) reports that econometric models often contain heteroscedasticity and autocorrelation of "unknown form" and that it is extremely important to use simultaneous heteroskedastic and autocorrelation consistent (HAC) estimators prior to statistical inference. Therefore, we applied the Newey and West (1994) procedure—using parameters specified by Stock and Watson (2002) —to correct for potential heteroscedasticity and/or serial correlation simultaneously. The presence of non-stationary, time-series data in econometric models can lead to spurious regression results (Granger and Newbold, 1974). Conversely, the presence of raw or transformed data that is stationary increases the likelihood that the forecast will produce meaningful results. For this reason, we tested for the presence of unit roots and then addressed any issues related to non-stationarity, if present. The technical appendix shows that the preferred models used in this analysis are stationary. Larsen et al. (2015) and Larsen (2016a) contain more information on the foundational model specification and relevant testing procedures.

be consistent with the spatial granularity of other research identified in the U.S. national climate assessments (NCA). Figure 1 shows the multi-state regions that were used in this analysis, which correspond with those being used in the next NCA.

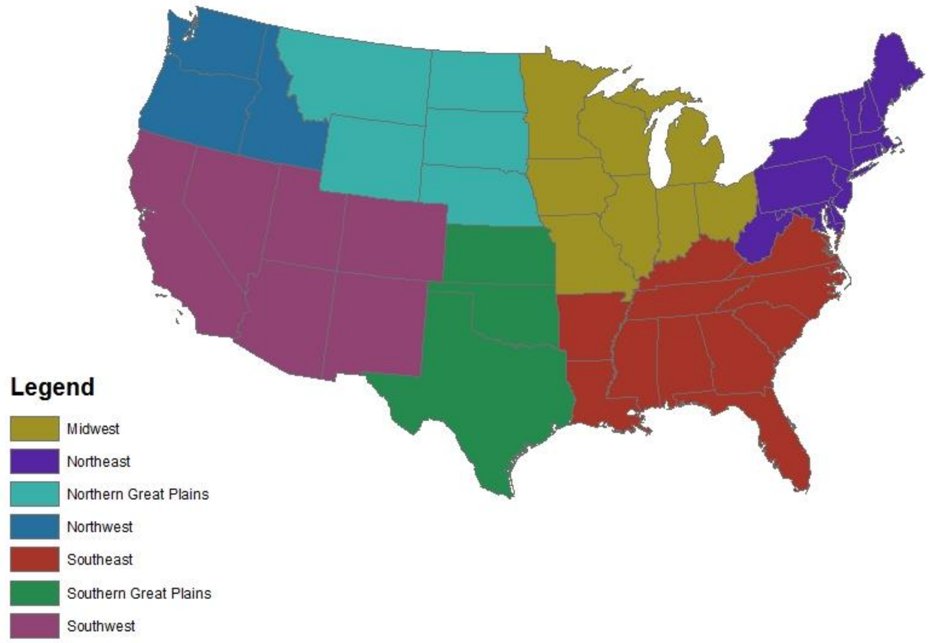

Figure 1. Regions used in this analysis

More specifically, the mean of the coefficients for the utility-level effects (i.e., intercepts) were calculated at a regional level to coincide with the NCA regions. Equation (4) shows how the regional model intercepts (β_r) were calculated by averaging the utility effects (α_i) for all of the sampled utilities (n) located in the respective NCA region (r)[3].

$$\beta_r = \frac{\sum_i^n \alpha_i}{n} \ : i \in r \tag{4}$$

B. Forecasting regional power system reliability

It follows that regional SAIFI and SAIDI can be forecasted by inserting values for the regional intercepts (βr) introduced in equation (4) and an array of explanatory variables (X) into the model framework described in equation (3). In some cases, future values of the explanatory variables were held constant based on historical information (e.g., presence of outage management system) and in other cases (e.g.,

3 Missing values for utility customers per line mile, T&D line O&M expenditures, and line miles underground were substituted with average regional values per year. This effort to balance the panel data—prior to running the regression—led to a significantly larger sample of utilities included in the resulting regional specification. Additional details, including the regression results, are included in the Technical Appendix.

weather-related explanatory variables), the future values were allowed to change over time. This analysis focuses on the impact of explanatory variables related to severe weather, O&M expenditures, and the rate at which power systems are undergrounded.

Future regional power system characteristics impacting reliability

As noted earlier, the purpose of this study is to evaluate changes to long-term power system reliability—and any associated interruption costs—under alternative futures. Accordingly, we include state-of-the-art projections of severe weather-related explanatory variables and generally project long-term values for other power system characteristics. More specifically, average annual electricity sales, utility O&M expenditures, average customers per line mile, share of underground line miles, and the presence of outage management systems were estimated through the forecast horizon by holding these values equal to the 15-year regional historical values.

Future regional climate impacting reliability

This analysis estimates changes in future severe weather metrics under ten scenarios – two "representative concentration pathways" (RCPs) that capture a range of plausible futures for five Atmosphere-Ocean General Circulation Models (AOGCMs). The RCPs are identified by their approximate total radiative forcing in the year 2100, relative to 1750: 8.5 W/m^2 (RCP 8.5) and 4.5 W/m^2 (RCP 4.5). RCP 8.5 implies a future with continued greenhouse gas emissions growth, whereas RCP 4.5 represents a global greenhouse gas reduction scenario.

The fifth phase of the Coupled Model Inter-comparison Project (CMIP5; Taylor et al. 2012) developed a large inventory of climate simulations using AOGCMs driven by these RCPs. As in most impacts work, the selection of a subset of AOGCMs was necessary due to computational and resource constraints. As such, five AOGCMs were chosen with the intent of ensuring that the subset captures a large range of the variability in climate outcomes observed across the entire CMIP5 ensemble. The five selected AOGCMs (CCSM4, GISS-E2-R, CanESM2, HadGEM2-ES, and MIROC5) cover a large range of the variability across the entire ensemble in terms of annual and season temperature and precipitation. This subset also balances the range alongside considerations of model independence, broader usage by the scientific community, and skill.

The simulations from these five CMIP5 AOGCMs are available at a relatively coarse grid cell resolution (roughly 2.5˚x 2.0˚). To provide more localized projections of severe weather variables (e.g., precipitation) and to employ projections that are statistically consistent with the historic period (defined in this analysis as 1986-2005), the Localized Constructed Analogs dataset (LOCA; Pierce et al. 2014; U.S. Bureau of Reclamation 2016) was employed. The LOCA downscaled dataset provides daily maximum temperature, daily minimum temperature, and daily precipitation values at 1/16 degree resolution from 2006-2099. Details describing steps taken to process the specific variables used in this analysis are shown in Table 1. The initial LOCA dataset did not provide two variables needed for this analysis: wind speed and lightning strikes.

Table 1. Processing of LOCA Variables

Variable	Input	Output	Process
Heating Degree Days (HDD) and Cooling Degree Days (CDD)	spatial: 1/16th degree temporal: daily LOCA variables: tmin (°C), tmax (°C)	spatial: NCA region temporal: annual variables: HDD and CDD	1. Calculate daily tmean using an average of tmin and tmax 2. Calculate annual HDD and CDD using a threshold of 65 degrees Fahrenheit[4] 3. Spatially aggregate data from 1/16th degree to NCA regional resolution, and from daily to annual.
Precipitation	spatial: 1/16th degree temporal: daily LOCA variables: pr (mm)	spatial: NCA region temporal: annual variables: precip (mm)	Spatially aggregate data from 1/16th degree to NCA regional resolution, and from daily to annual.

Wind speed projections were constructed at a 0.5 degree resolution using a statistical approach that relies on wind speed, temperature, and precipitation from the Princeton land surface dataset (Sheffield et al. 2006) and LOCA values for temperature and precipitation.[5]

The rate of cloud-to-ground lightning strikes was calculated using the product of convective available potential energy (CAPE) and precipitation (P) as a local proxy for lightning (Romps et al., 2014). The constant of proportionality relating the lightning strike rate to CAPE x P was found by comparing each model's average CAPE x P over the continental U.S. during a historical period to the observed lightning strike rates during that same period (for details, see Seeley and Romps 2017). Next, the lightning strike data were spatially averaged from the native resolution of the AOGCMs to the NCA regions.

In order to reduce the effects of inter-annual variability and obtain results that are better representative of a particular point in the future, this analysis used 20-year eras centered on specific years of interest: 2030 (2020-2039), 2050 (2040-2059), 2070 (2060-2079), and 2090 (2080-2099). Table 2 describes the source of the historical and future information used when forecasting long-run regional power system reliability.

[4] Annual HDD and CDD are calculated first by calculating degrees above or below the threshold value of 65 degrees for each day, and then summing the degrees above the threshold to compute annual HDD, and degrees below the threshold to compute annual CDD.

[5] Absent a bias-corrected set of wind speed projections for 2006 to 2099, these were generated using a statistical approach. The approach related historical wind speed to historical temperature and precipitation from the Princeton dataset (Sheffield et al. 2006), and then used this relationship to calculate projected wind speed based on projected LOCA precipitation and temperature.

Table 2. Comments on historical and future values used in regional models of power system reliability

Data	Description	Comments on historical data source(s)	Comments on future values
SAIDI/SAIFI	Annual reliability metrics	Direct communication and/or web search of public utility commissions and utilities	See following page(s)
Sales	Annual retail electricity sales per customer	U.S. Energy Information Administration (EIA) via Form 861	Using sales as a proxy for consumption and held constant at historical, regional average values
Expenditures	Annual T&D O&M expenditure data per customer	FERC Form 1; U.S. Department of Agriculture Rural Utilities Service Form 7	Held constant at historical, regional average values
Post OMS/OMS	Presence of outage management system (OMS) and years since installation	Direct communication and/or web search of public utility commissions and utilities	Held constant at historical, regional average values
Cold	Abnormally high number of annual heating degree-days	National Oceanic & Atmospheric Administration's National Centers for Environmental Information	Estimated using output from the LOCA downscaled dataset (Pierce et al. 2014)
Warm	Abnormally high number of annual cooling degree-days	National Oceanic & Atmospheric Administration's National Centers for Environmental Information	Estimated using output from the LOCA downscaled dataset (Pierce et al. 2014)
Lightning	Abnormally high number of lightning strikes	Vaisala National Lightning Detection Network	Estimated using the CAPE x P proxy as described in Seeley and Romps (2017)
Wind/Wind^2	Abnormally high annual average wind speeds	National Oceanic & Atmospheric Administration's National Centers for Environmental Information	Estimated using output from LOCA downscaled dataset (Pierce et al. 2014) and Princeton land surface dataset (Sheffield et al. 2006)
Wet	Abnormally high total annual precipitation	National Oceanic & Atmospheric Administration's National Centers for Environmental Information	Estimated using output from the LOCA downscaled dataset (Pierce et al. 2014)

Data	Description	Comments on historical data source(s)	Comments on future values
Dry	Abnormally low total annual precipitation	National Oceanic & Atmospheric Administration's National Centers for Environmental Information	Estimated using output from the LOCA downscaled dataset (Pierce et al. 2014)
Population density	Customers per T&D line mile	FERC Form 1; U.S. Department of Agriculture Rural Utilities Service Form 7	Estimated using the Median Variant Projection of the United Nation's World Population Prospects dataset (UN 2015), downscaled to U.S. counties using the Integrated Climate and Land Use Scenarios (ICLUS, version 2) model (USEPA 2016).
Underground line share	Percentage share of underground T&D line miles relative to total T&D line miles	FERC Form 1; U.S. Department of Agriculture Rural Utilities Service Form 7	Underground line mile share held constant historical regional average for undergrounding business-as-usual scenario; aggressive undergrounding scenario modeled following logistic pathway (see Section C).

Projecting interruption frequency and typical duration

Next, future annual estimates of the explanatory variables (see Table 2) were inputted into the regional models of power system reliability. This step resulted in projections for both the regional frequency and total annual minutes that an average customer was without power in a given future year. We considered four different models of power system reliability in this analysis. Models 1 and 2 are featured in the results section, and models 3 and 4 are presented in Technical Appendix C. Models 1 and 2 are featured, because these models represent the highest and lowest cost estimates across the four models considered, respectively.

Model 1 includes the Larsen et al. (2016) parameters of SAIFI including all weather-related explanatory variables and the Larsen et al. (2016) model parameters of SAIDI, but without the abnormally (1) high

HDD, (2) high CDD, and (3) low precipitation explanatory variables[6]. In model 1, the coefficient on the year variable—for both the SAIDI and SAIFI models—follows an exponential growth rate from 1986-2005 and then a linear growth rate thereafter. In other words, we assumed that SAIFI and SAIDI would not continue to worsen at an exponential rate through the end of the century. We made this assumption, because we could not envision a future where a typical utility customer is without power for months at a time—a result that occurs if we assume that reliability (SAIDI) continues to worsen at the exponential rates observed in the recent past. Model 2 is configured the same as model 1, but it assumes that there is no linear time trend starting in 2006. Model 3 is similar to model 1, but in this case, the abnormally (1) high HDD, (2) high CDD, and (3) low precipitation were also removed from the SAIFI regression. Model 4 is configured the same as model 3, but it assumes that there is no linear time trend starting in 2006.

C. Future power system interruption costs

Research by Sullivan et al. (2009; 2015) provides the foundation for estimating the costs of power interruptions to customers. Sullivan et al. (2009) compiled information from ~30 value-of-service reliability studies undertaken by 10 U.S. electric utilities from 1989 to 2005 indicating that:

> "…because these studies used nearly identical interruption cost estimation or willingness-to-pay/accept methods it was possible to integrate their results into a single meta-database describing the value of electric service reliability observed in all of them. Once the datasets from the various studies were combined, a two-part regression model was used to estimate customer damage functions that can be generally applied to calculate customer interruption costs per event by season, time of day, day of week, and geographical regions within the U.S. for industrial, commercial, and residential customers."

In other words, a number U.S. utilities have conducted surveys to determine residential customer willingness to pay (accept) to avoid (incur) power interruptions. Researchers used the results from these surveys as well as direct cost measurements to develop the ICE Calculator. Results from the ICE

[6] We considered power system reliability models both with and without including temperature and abnormally low precipitation explanatory variables due, in part, to the research of Hines et al. (2009), Alvehag and Söder (2011), Ward (2013), LaCommare et al. (2017), and others. Hines et al. (2009) evaluated power system disturbances in the U.S. and Canada and found that wind/rain, ice storms, hurricanes, tornadoes, and lightning were the main weather-related causes of interruptions from 1984-2006. Alvehag and Söder (2011) only consider abnormally high wind speeds and lightning strikes in their model of distribution system reliability. Ward (2013) found that high winds, storms, hurricanes, ice, snow, lightning, rain, floods, and landslides are the primary weather-related causes of power interruption frequency and duration. Drought and temperature effects were are also discussed by Ward (2013), but their direct impact was limited to reducing the power rating (i.e., capacity) of T&D equipment. It was noted, however, that drought conditions can increase the chance of fires which can indirectly lead to interruptions (Ward 2013). LaCommare et al. (2017) provide anecdotal evidence that utility crews in Washington D.C. took extra precautions during an excessive heat wave, but it was unclear whether these precautions led to longer response times. For this analysis, we assume that abnormally warm (or cold) temperatures and low precipitation will (Model 1) or will not (Model 2) directly impact the annual frequency or interruptions, but that these specific weather-related metrics will not have a direct impact on the total annual restoration time for customers.

Calculator were combined with regional, long-term projections of power interruptions to estimate the total interruption costs to customers under a number of scenarios.

Several inputs are necessary in order to estimate individual interruption costs for different types of customers. Equation (5), below, shows that individual interruption costs (ICE)—by customer class—are a function of the regional average mix of residential, small, and medium/large commercial and industrial customers (MixCust); median household income by region (Income); annual electricity consumption (Consumption); and the average duration of an individual interruption, or Customer Average Interruption Duration Index (CAIDI).

$$\mathrm{ICE}_{crst} = f\left(\mathrm{MixCust}_{crt}, \mathrm{Income}_{crt}, \mathrm{Consumption}_{crt}, \widehat{\mathrm{CAIDI}}_{rst}\right) \quad (5)$$

First, the regional average duration of an individual interruption can be estimated by dividing the future projections of SAIFI from SAIDI (see previous section) to produce a long-term projection of CAIDI—see equation (6).

$$\widehat{\mathrm{CAIDI}}_{rst} = \frac{\widehat{\mathrm{SAIDI}}_{rst}}{\widehat{\mathrm{SAIFI}}_{rst}} \quad (6)$$

Next, the share of customers by customer class and NCA region was estimated by using a mix of actual historic data (1990-2014) together with the Median Variant Projection of the United Nation's World Population Prospects dataset (UN 2015) downscaled to U.S. counties using the Integrated Climate and Land Use Scenarios (ICLUS, version 2) model (U.S. EPA 2016) to project the out years (2015-2100). The future share of customers by end-use sector was estimated using the historical ratio of regional customers—by end use (EIA 2016b)—to regional population, forecasting this ratio of customers to population, and applying the forecasted ratio to long-term population. See Figures B-1 through B-3 in the Technical Appendix for plots of the observed and projected number of customers by NCA region. Table 3 describes the source of the historical and future information used in the ICE calculator.

Household income by NCA region was estimated by applying a customer weighting to each state median income to derive a regional average for each historic year (1984-2014). The historical data is then linearly regressed to forecast years 2015-2100 (see Figure B-4 in Technical Appendix; U.S. Census Bureau 2016).

Electricity sales data from the U.S. DOE Energy Information Administration (EIA) Form 861 was used as a proxy for annual customer consumption. Electricity sales are reported by utility and used to estimate regional electricity consumption per customer for all of the utilities reporting via EIA 861. Historical regional consumption by customer (2005-2014) is then used to derive a 10-year average value that is applied in projecting the annual values through 2100. See Figure B-5 through Figure B-7 in the Technical Appendix (EIA 2016b).

Table 3. Comments on historical and future values used in the ICE calculator

Data	Description	Comments on historical data source(s)	Comments on future values
CAIDI	Annual reliability metrics	N/A	Estimated by authors by dividing projected SAIFI by SAIDI.
Customers	Electricity customers by end-use sector and region	U.S. Energy Information Administration (EIA) via Form 861	Downscaled to U.S. counties using the ICLUS (version 2) model. Forecasted years 2015-2100 follow the same growth rate as population density – see Table 2. The share of customers by class use a linear projection of the historic number of customer in each class (EIA 2016b)
Consumption	Electricity sales as a proxy for consumption by end-use sector and region	U.S. Energy Information Administration (EIA) via Form 861	A weighted average—by end-use and region—of the last ten historical years (2005-2014) are used to estimate annual values over the forecast horizon (2015-2100).
Household income	Median household income by region	U.S. Census Bureau (2016)	Historical years (1986-2014) are linearly regressed to estimate median, regional household income over the forecast horizon (2015-2099).
Manufacturing	Share of commercial and industrial customers in the manufacturing sector	Historical average based on utility customer surveys as reported by Sullivan et al. (2015)	Future values held constant at 7.8% share.
Construction	Share of commercial and industrial customers in the construction sector	Historical average based on utility customer surveys as reported by Sullivan et al. (2015)	Future values held constant at 4.6% share.

The annual value of total interruption costs (TIC)—by scenario and region—can be estimated by multiplying the projected frequency of interruptions (SAIFI) against the average interruption cost (ICE) for each customer class and the number of customers (Customers) in each class (see equation 7).

$$\mathrm{TIC}_{rst} = \sum_{c=1}^{3} \mathrm{SAIFI}_{rst}(\mathrm{Customers}_{crt})(\mathrm{ICE}_{crst}) \tag{7}$$

D. Estimating total customer costs with aggressive undergrounding and O&M expenditures

It is assumed that planners make strategic decisions based on recent and expected impacts to the power system from future weather. In the aggressive undergrounding case, power system planners and policymakers—at the local, state, regional, and national level—have perfect foresight and immediately mandate and implement proactive strategies intended to reduce the frequency, typical duration, and the cost of power interruptions to customers. Given this assumption, two model parameters are adjusted over time in an attempt to offset some of the future risk associated with power system interruptions.

First, future underground line mile share—by region—is set to follow a logistic function (see Equation (8), which has been used to capture the long-term diffusion of infrastructure (e.g., see Grübler 1990 and Samaras 2008). In this equation, *Underground* represents the share of line miles that are undergrounded for each region (r) at time (t), t_0 is the future point in time (i.e., inflection point) when the growth rate slows, and ρ is a parameter specifying the curve's growth rate.

$$\hat{\mathrm{Underground}}_{rt} = \begin{cases} \overline{\mathrm{Underground}_r}, \text{ if } t \leq 2005 \\ \overline{\mathrm{Underground}_r} + \left(\dfrac{100 - \overline{\mathrm{Underground}_r}}{1 + e^{-(\rho(t-t_0))}} \right), \text{ if } t > 2005 \end{cases} \tag{8}$$

Before 2006, it is assumed that the share of undergrounded line miles to total line miles is equal to the regional historical average (see Table 2). Starting in 2006, however, the underground line mile share increases above the regional historical average until the point in time when the underground line mile share relative to total line miles hits 100% (i.e., all T&D lines are underground in each region). Larsen (2016a; 2016b) showed that as overhead lines hit the end of their useful lifespan and are replaced with underground lines, then the percentage share of underground line miles—to total line miles—increases approximately following a logistic function with a relatively small ρ parameter (i.e., growth rate) and annual inflection point (t_0) of approximately twenty five years after starting the overhead-to-underground replacement cycle[7]. Accordingly, the undergrounding algorithm is initially configured with a ρ value of 0.1 and a t_0 value of 2030, which is approximately 25 years after this model begins

[7] See Figure 26 in Larsen (2016a).

estimating severe weather-related impacts of power interruptions. Figure 2 shows the rate at which overhead lines are converted to underground lines in this model.

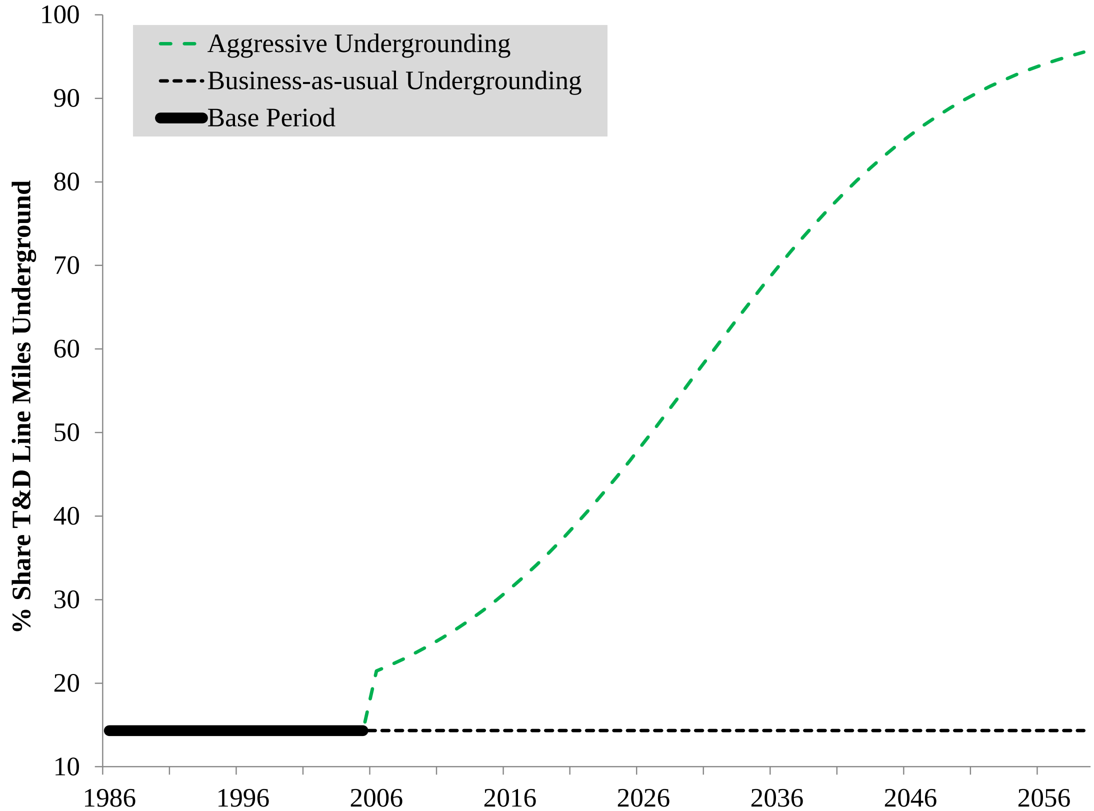

Figure 2. Increasing line miles underground

A second risk management component assumes that utilities—across the country—aggressively increase their annual O&M spending per customer in anticipation of significant severe weather-related impacts[8]. Increased O&M spending is a proxy for a number of risk management measures, which may include additional O&M costs associated with undergrounding power lines, aggressive vegetative management practices, proactive T&D line maintenance, increased staffing-levels, and other strategies to offset risk. Equation 9 shows that annual O&M expenditures are held constant at historical regional levels before 2006. After 2006, however, annual O&M expenditures are compounded annually at a growth rate, θ[9].

[8] The capital costs associated with widespread undergrounding of the Continental U.S. power system are assumed to be at parity with the capital costs incurred to install overhead lines. Larsen (2016a; 2016b) show that capital cost parity—between overhead and underground lines—was achieved in a rural setting (Cordova, Alaska). However, future revisions to this model might involve including alternative capital cost assumptions for overhead and underground lines. It follows that this type of revision to the model would change the costs and associated net benefits of utility efforts to reduce risks to T&D lines.

[9] Larsen (2016b) assume that distribution line O&M costs increase linearly at a rate of 0.5% times the capital cost of the line per year. However, Larsen (2016b) also notes that it is "likely that actual infrastructure O&M expenses increase (decrease) over time in a non-linear fashion". In this model, O&M costs grow at a compounding (non-linear) rate of 0.5% per year and that all O&M cost increases are passed along to customers.

$$\overset{\wedge}{\text{Expenditures}}_{rt} = \begin{cases} \overline{\text{Expenditures}_r}, \text{ if } t \leq 2005 \\ \overline{\text{Expenditures}_r} + \theta(t\text{-}2005)(\overline{\text{Expenditures}_r}), \text{ if } t > 2005 \end{cases} \qquad (9)$$

Figure 3 shows the total increase in annual O&M costs for the national model of power system interruption costs

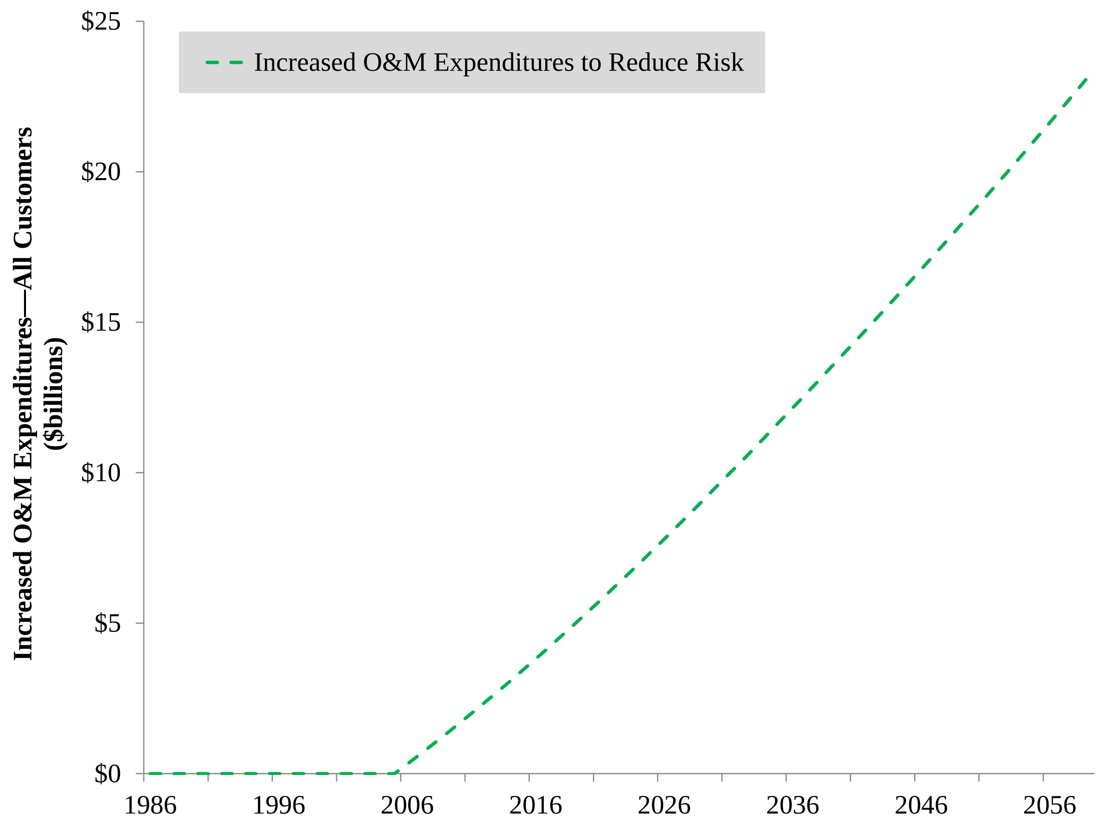

Figure 3. Increased annual O&M expenditures (national model)

It follows that future values of SAIFI (equation 5) and SAIDI (equation 6)—and any associated costs of interruptions—can be re-estimated with the increased annual underground line mile share and O&M expenditures assumptions. These proactive expenditures reduce future power interruption costs, but at an expense to customers that is equivalent to the increase in O&M costs above the historic average. Equation (10) shows that the total costs of increasing O&M expenditures (TIMC) in any given year are a function of the increased annual O&M spending (see equation 9) and the regional count of commercial, industrial, and residential customers (Customers)[10].

[10] Regional expenditures per customer are multiplied by 1,000, because the units being used in the reliability equations are reported in thousands of O&M dollars per customer.

$$\mathrm{TIMC_{rt}} = \sum_{c=1}^{3} (\mathrm{Customers_{crt}})(\widehat{\mathrm{Expenditures}}_{\mathrm{rt}})(1000) \tag{10}$$

Thus, the net benefit of risk reduction efforts[11] is simply the reduction in power system interruption costs—net of any additional O&M costs associated with reducing risk—for all combinations of regions and scenarios. It follows that the total costs to customers (TC) can be expressed by summing the total costs related to power interruptions (TIC) and the increased O&M expenditures to reduce risk (total increased maintenance cost or TIMC) (see equation 11).

$$\mathrm{TC_{rst}} = \mathrm{TIC_{rst}} + \mathrm{TIMC_{rt}} \tag{11}$$

Finally, total annual costs to customers are discounted back to the present ($2015) using an annual discount rate of 3% to determine the net present value (NPV). We applied the same discount rate as other federally-funded studies that used a consistent set of atmosphere-ocean general circulation models, RCPs, and long-term population assumptions (U.S. EPA 2015).

3. Results

In this section, we report estimates of the future and present value of the total costs to customers from power interruptions. Here we present the two preferred models[12] discussed earlier that individually include a base case scenario (1986-2005) and the results of two RCP scenarios, representing the mean of the five AOGCM models, with and without aggressive utility risk reduction efforts.

A. Frequency and duration of interruptions

Figure 4 shows that the frequency and total average duration of power interruptions are projected to increase (model 1) or remain stable (model 2) over the coming decades if planners continue to follow traditional planning assumptions. However, increasing both the share of underground line miles and annual O&M expenditures leads to relative improvements in power system reliability—especially in reducing the total average duration customers are without power (SAIDI).

[11] As noted earlier, it is assumed that utilities will pass along all increases in future O&M spending to their customers. For this reason, increased annual O&M spending is added to customer interruption costs so that both the costs and benefits (i.e., reductions in power interruption frequency and duration) of efforts to reduce utility risk are properly accounted for.

[12] Model 1: Larsen et al. (2015) model of SAIDI does not include abnormally (1) high HDD, (2) high CDD, and (3) low precipitation; Both SAIDI and SAIFI models include linear time trend starting in 2006. Model 2: Similar to model 1, but without linear time trend starting in 2006.

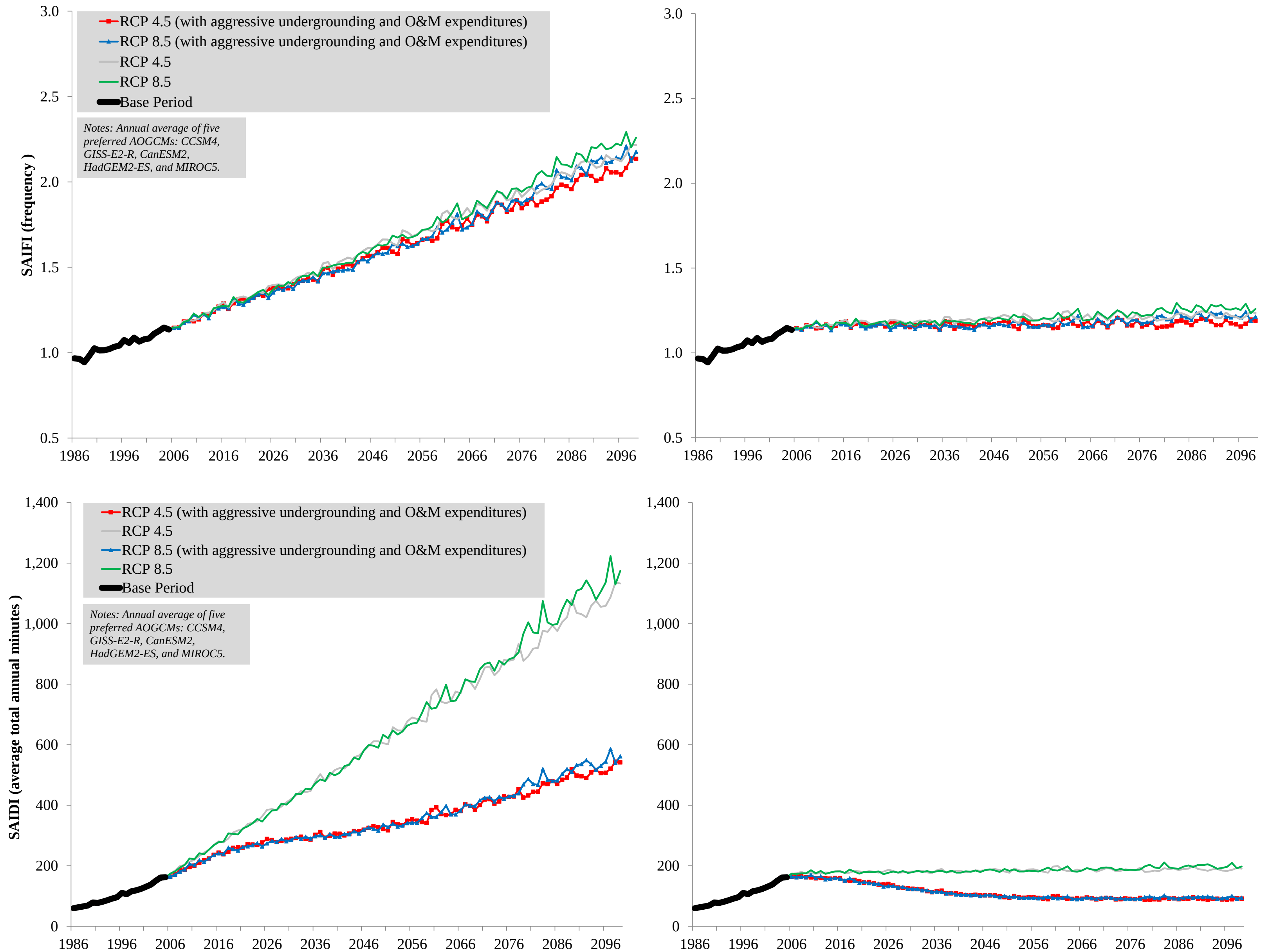

Figure 4. Projected SAIFI (top) and SAIDI (bottom) for models 1 (left) and 2 (right)

B. Annual costs for all U.S. customers

Figure 5 shows projected annual costs (top) and costs per customer (bottom) for national models 1 (left) and 2 (right). Through ~2060, customer costs related to power interruptions are generally higher under RCP 4.5 when compared to RCP 8.5. After 2060, however, the impact of abnormal (as defined with respect to historical levels) precipitation, lightning strikes, and wind speeds eventually drives the RCP 8.5 customer costs above those estimated under RCP 4.5.

Through the end of the century, model 1 shows that increasing the share of underground line miles and O&M spending reduces total customer costs (recall that customer costs equal interruption costs increased O&M expenditures) relative to the case where aggressive undergrounding and increased O&M spending did not occur.

In model 2, the benefits of aggressive undergrounding and increased O&M expenditures slightly outweigh the costs through the middle of century. However, after ~2060, the increased O&M costs—which are passed along to customers—exceed any benefit from the avoided interruption costs. This finding implies that in the absence of an increasing, long-term trend of worsening reliability, some long-term efforts to reduce risk are not always cost-effective. Interestingly, removing the annual time trend decreases the magnitude of future customer costs—relative to model 1—by a factor of ~6.

Figure 6 depicts average annual costs by era for models 1 and 2 both with and without discounting. These results include the average value (top of bar), the minimum (bottom of whisker) and maximum (top of whisker) values due to variation across the five preferred climate models.

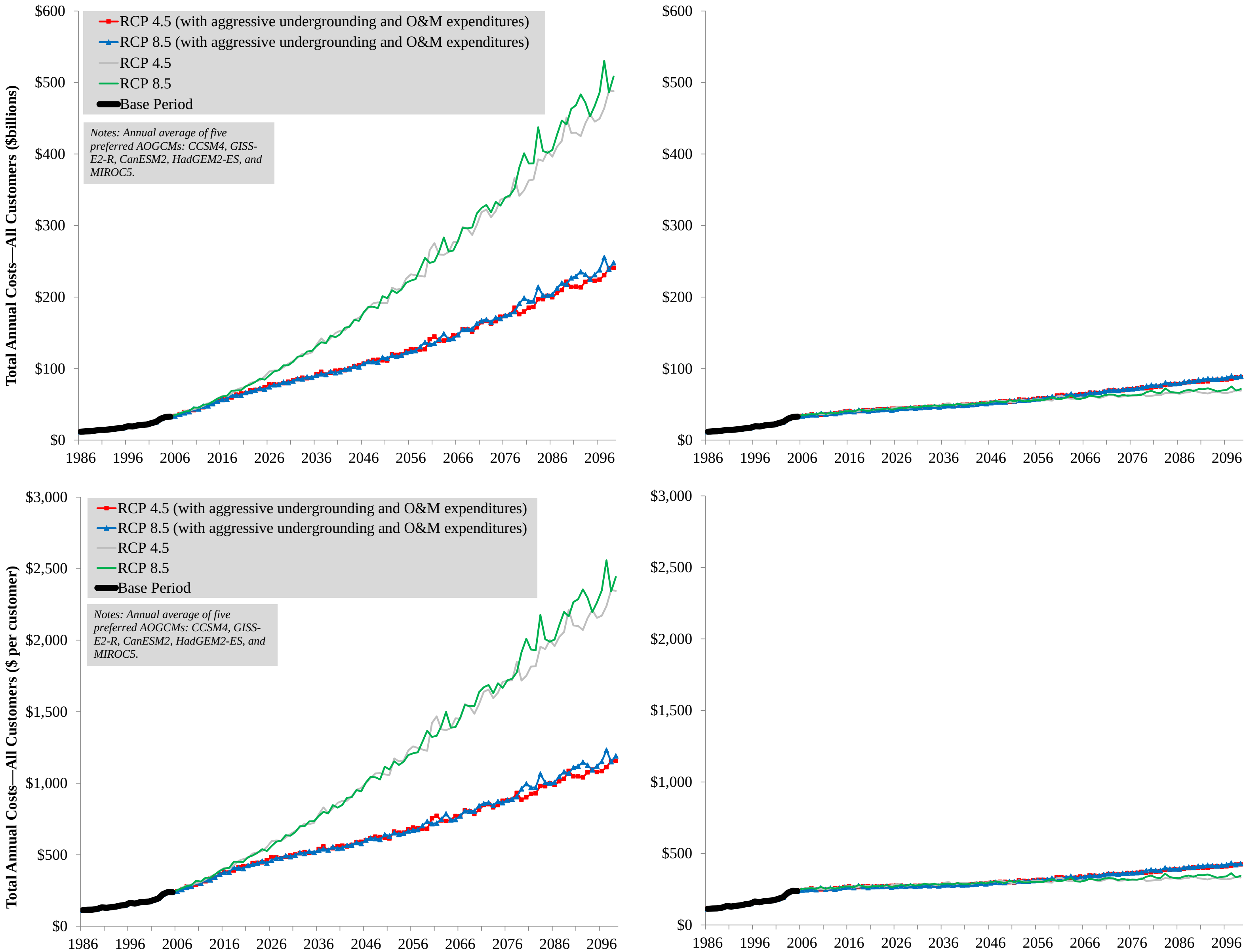

Figure 5. Projected annual costs (top) and costs per customer (bottom) for models 1 (left) and 2 (right)

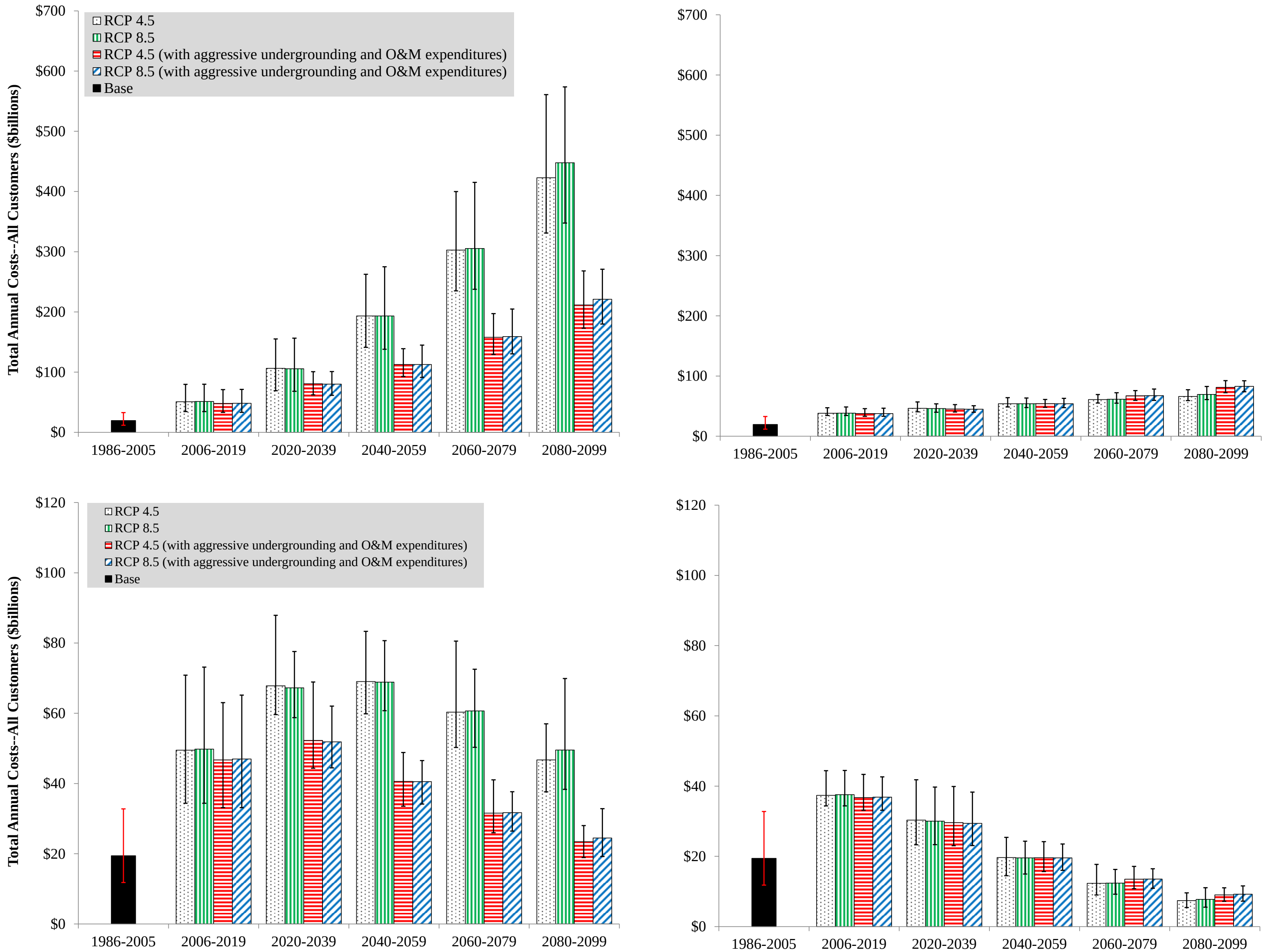

Figure 6. Annual costs by era (not discounted; top) and annual costs by era (discounted 3%; bottom) for models 1 (left) and 2 (right)[13]

[13] Bar heights represent era average of the five preferred AOGCMs. Whiskers represent minimum and maximum era results from AOGCMs.

C. Cumulative costs for all U.S. customers

Table 4 and Table 5 show that cumulative costs—through 2099—are higher under RCP 8.5 when compared to RCP 4.5. However, the cumulative differences do not begin accruing until after ~2060.

Table 4. Cumulative costs for model 1 through middle and end-of-century—without and with aggressive undergrounding and O&M expenditures[14]

Model 1	*2015-2059*				*2015-2099*			
	Without aggressive undergrounding and O&M expenditures		*With aggressive undergrounding and O&M expenditures*		*Without aggressive undergrounding and O&M expenditures*		*With aggressive undergrounding and O&M expenditures*	
Metric (trillions of $2015)	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Cumulative Costs	$6.70	$6.69	$4.54	$4.53	$21.21	$21.75	$11.93	$12.13
NPV Cumulative Costs	$3.43	$3.42	$2.51↑	$2.51	$5.57	$5.62	$3.61	$3.63

Cumulative customer costs, through the middle of the century, are $1.52-$3.43 trillion ($2015; NPV) and $1.50-$2.51 trillion without and with aggressive undergrounding and O&M expenditures, respectively. By the end of the century, cumulative customer costs are $1.92-$5.62 trillion (without aggressive undergrounding and O&M expenditures) and $1.95-$3.63 trillion (with aggressive undergrounding and O&M expenditures).

Table 5. Cumulative costs for model 2 through middle and end-of-century—without and with aggressive undergrounding and O&M expenditures

Model 2	*2015-2059*				*2015-2099*			
	Without aggressive undergrounding and O&M expenditures		*With aggressive undergrounding and O&M expenditures*		*Without aggressive undergrounding and O&M expenditures*		*With aggressive undergrounding and O&M expenditures*	
Metric (trillions of $2015)	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Cumulative Costs	$2.54	$2.53	$2.51↑	$2.51	$5.08	$5.15	$5.48	$5.51
NPV Cumulative Costs	$1.52↑	$1.52	$1.50↑	$1.50	$1.92	$1.92↑	$1.95	$1.95↑

[14] Upward pointing arrow (↑) indicates that rounding has masked a value that is slightly higher than a corresponding value.

D. Regional costs

The annual and cumulative costs to customer can also be represented at the NCA region level. Figure 7 depicts the annual costs for models 1 and 2 without and with aggressive undergrounding and O&M expenditures for RCP 8.5. Over time and across models, annual costs to customers increase at a relatively higher rate for the Southeast and Southwest NCA regions. Figure 8 generally confirms the findings discussed earlier—that is, the costs are initially higher under RCP 4.5, but the impact of abnormal precipitation, lightning strikes, and abnormally high average wind speeds eventually drives the RCP 8.5 customer costs above those estimated under RCP 4.5 by the end of the century. All regions of the country—with the exception of the Pacific Northwest region—confirm this finding. Figure 9 shows cumulative costs through the end of the century for both RCP 4.5 and RCP 8.5. Again, impacts are most pronounced in the Southeast NCA region. It is important to note, however, that the regional differences between RCP 8.5 and 4.5 are relatively small—as reflected in the maps.

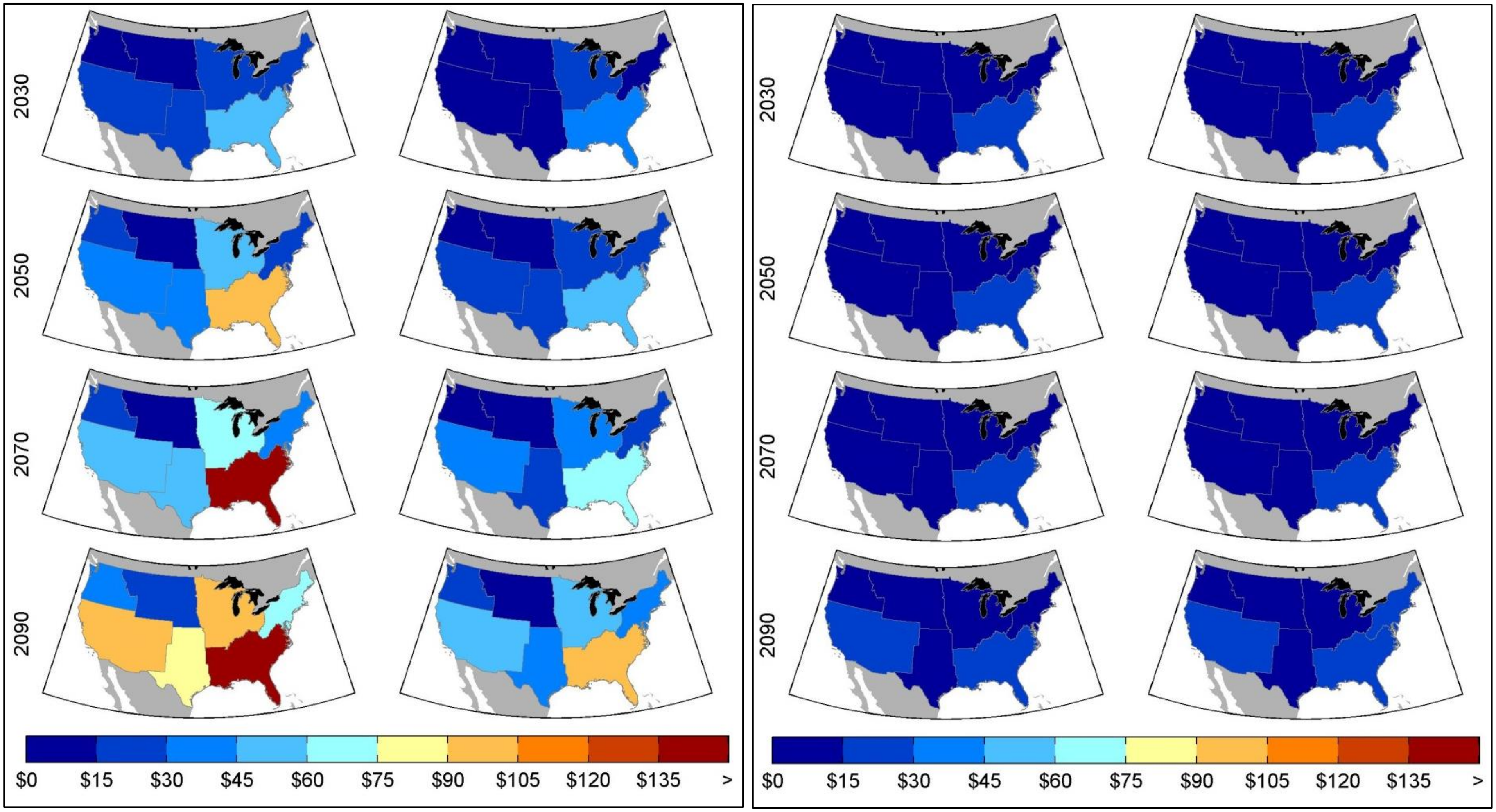

Figure 7. Annual costs for models 1 (left box) and 2 (right box) without (left inside) and with aggressive undergrounding and O&M expenditures (right inside); RCP 8.5; billions of $2015 (undiscounted)

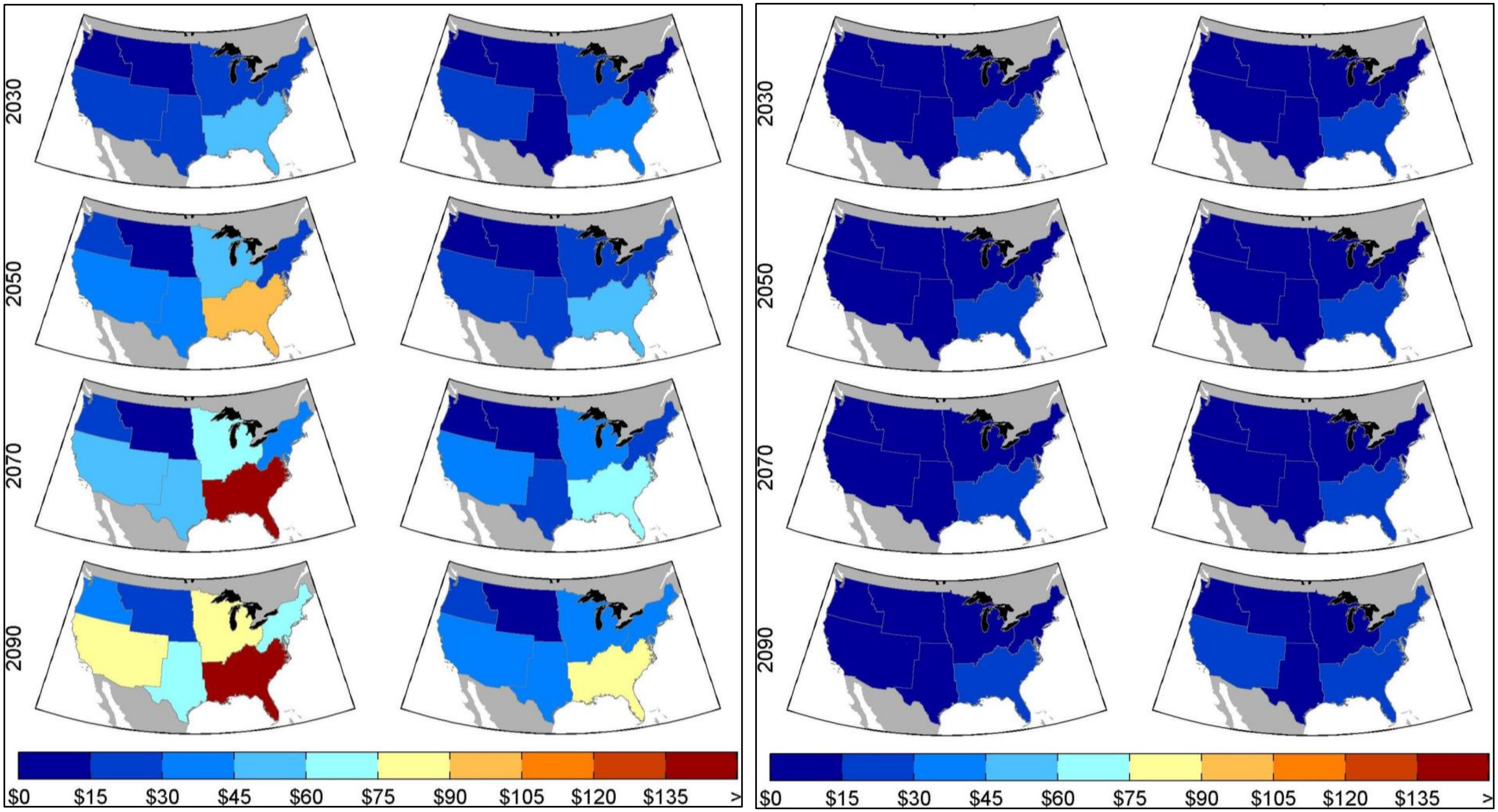

Figure 8. Annual costs for models 1 (left box) and 2 (right box) without (left inside) and with aggressive undergrounding and O&M expenditures (right inside); RCP 4.5; billions of $2015 (undiscounted)

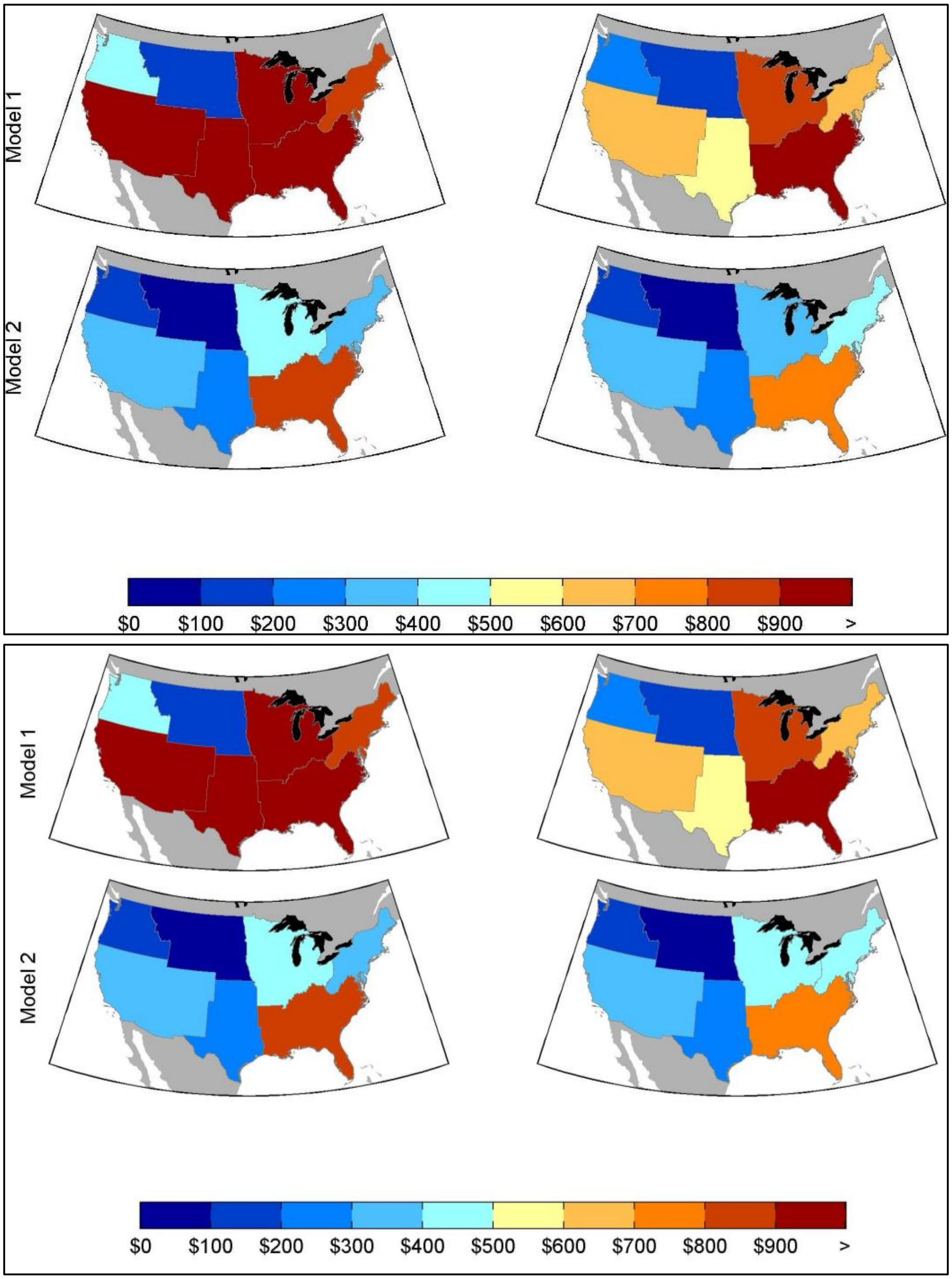

Figure 9. Cumulative costs through end-of-century for RCP 8.5 (top box; billions of $2015) and RCP 4.5 (bottom box) without (left inside) and with aggressive undergrounding (right inside)

4. Results in Context and Analysis Caveats

It is insightful to compare the results from this analysis to interruption cost estimates from earlier research. The Executive Office of the President (2013) provided a useful, summary table that highlights previous estimates of the annual cost of power interruptions. Table 6, below, is an updated and expanded version of that table. We find that total annual interruption costs estimated by our model fall within the range of estimates produced from earlier studies. This comparative analysis also shows that earlier estimates of interruption costs attributed directly or indirectly to severe weather are significantly higher than what were estimated with our model.

Table 6. Estimates of annual cost of power interruptions

Source	Estimate (billions of $2015)	Comments
All interruptions		
Swaminathan and Sen (1998)	$61	Excludes commercial and residential sectors
Primen, Inc./EPRI (2001)	$136 to $216	Excludes cost of outages to residential customers
LaCommare and Eto (2006)	$29 to $174	Includes both momentary and sustained interruptions
This study	*$30 to $50*	*Range of annual interruption costs from 2003-2012; contiguous U.S. only*
Severe weather-related interruptions		
Campbell (2012)	$26 to $72	Back-of-the-envelope calculation that used the Primen, Inc./EPRI estimate of total cost of interruptions
Executive Office of the President (2013)	$5 to $77	Range of annual interruption costs from 2003-2012; entire U.S.; includes cost estimates for actual superstorms
This study	*$2 to $3*	*Assumes that 6.4%*[15] *of total interruption cost can be explained by severe weather*

It is important to note, however, that there are significant differences in how the other back-of-the-envelope calculations capture costs (e.g., entire U.S., additional cost categories, estimates for individual Superstorms). LaCommare and Eto (2006), noted that "… widespread power losses resulting from major natural events (primarily storms but also hurricanes and earthquakes) are sometimes not included in the same [reliability metric] data categories as more routine power losses. As a result, power losses from natural events are not always included in data used for cost estimates." It is likely that the relative

[15] The reliability model regressions were run with and without the severe weather-related explanatory variables. Next, the adjusted r-squared values for the models without the weather regressors were subtracted from the models with the weather regressors included to estimate of the variation in interruption frequency and average total duration that can be explained by the severe weather metrics (6.4%). This percentage was multiplied against the total interruption cost to produce a back-of-the-envelope estimate of the annual dollar value of interruptions that can be attributed to these severe weather metrics.

impact of severe weather on outage costs is higher than what is reported in our model. We believe that this severe weather effect is being captured within the "unobservable" utility effects that are being controlled for as fixed effects within the underlying models of reliability.

Any attempt to project results that span the remainder of the century is based on a number of critical assumptions. The results from the models presented in this analysis are no exception. Accordingly, we discuss a number of analysis caveats that should be considered when interpreting the results and attempting to draw conclusions on the relative merits of prospective policies that attempt to improve power system reliability.

First, the underlying models of power system reliability are based on a relatively short time period (13 years)—and these models were used here to forecast well beyond their calibration period (2000-2012). And it is possible that the utilities used to calibrate the aforementioned models are a non-representative sample of utilities. That is, the 100+ utilities used to correlate SAIDI/SAIFI to a number of explanatory factors do not represent “typical” utilities within each NCA region. Furthermore, Larsen et al. (2015; 2016) note that the metrics to capture severe weather and utility T&D expenditures are imperfect, and that additional research is necessary to identify variables and supporting data most relevant to these effects. One key future research topic involves finding alternative severe weather metrics that have been previously unaccounted for, but are strongly correlated with power system reliability.

The replacement of aging power system infrastructure will certainly improve reliability over the coming years. It is also possible—or even likely—that a sequence of technological breakthroughs will occur which fundamentally change the trajectory of power system reliability across the U.S. and abroad. For example, a fully distributed power system—or even wirelessly-distributed electricity—could result in future generations experiencing fewer power interruptions. A number of researchers have indicated that distributed generation can provide customers with improved reliability (e.g., see Le et al. 2006; Chiradeja and Ramakumar 2004). Though the full-scale implementation of these potential technologies would likely reduce future costs, installation and maintenance of these technologies will require large investments by utilities. The models presented in this paper assume that risk reduction is exogenously determined. For the risk reduction scenario, it is known today that future power system reliability will continue to get worse, and there are only a limited number of options available to planners to reduce the impending impacts to customers (e.g., underground all existing and future overhead lines, increase utility O&M spending). Specifically, the future share of underground lines to overhead lines was assumed to follow a logistic function, increased O&M costs are compounded annually, and then these costs are passed on to customers. In reality, however, planners do not always know to what extent—or where—future risk will materialize. And there are a vast number of risk reduction options available beyond what was introduced in this paper (e.g., hardening of overhead line poles). For this reason, the actual benefits (and costs) of proactively responding to risk are likely to be different than what was presented in this analysis.

Monetizing changes in future power system reliability is also challenging for a number of reasons. Unfortunately, there is a general shortfall of research into the economic impacts of widespread and long duration power interruptions (Sanstad 2016). There is a need for this type of information to properly evaluate the societal costs and benefits (i.e., avoided costs) of resilient investments in power system infrastructure (LaCommare et al. 2017). More specifically, the models presented in this analysis do not consider the full economic impact of interruptions and the interruption cost estimates for long duration interruptions are capped at costs that would occur for a 16 hour interruption. Furthermore, only a relatively small number of U.S. utilities have conducted direct cost measurements or surveys to determine residential customer willingness to pay (accept) to avoid (incur) power interruptions (Sullivan et al. 2009; 2015). For this reason, there are questions about the accuracy of power system interruption cost estimates and the appropriateness of extending these estimates to other utility service territories. Furthermore, it is possible that long-term, structural changes in the electricity sector (e.g., environmental policies, widespread electric vehicle adoption) could fundamentally change customer costs associated with power interruptions. Finally, this research effort did not consider the future costs to utility customers from power interruptions occurring in Alaska and Hawaii.

5. Conclusion

In this analysis, we presented an integrated model—based on 13 years of data and research by Eto et al. (2012), Larsen et al. (2015; 2016) and Larsen (2016a)—that was developed and calibrated with the intent of forecasting regional power system reliability—and associated costs to customers—decades into the future. The integrated model includes a set of explanatory variables, including measures of abnormal weather; utility sales and O&M spending; share of underground line miles, etc., that were projected and then included in the regional models of power system reliability in order to project the long-term frequency and average annual duration of power interruptions under various scenarios. The annual frequency and average duration of each power interruption—as well as the regional mix of customer types and other electricity system characteristics—were then used to estimate the future costs of power interruptions for electric utility customers located across the Continental U.S. Finally, this integrated model was rerun to simulate the avoided interruption costs from increasing the percentage share of underground line miles and O&M spending—risk management strategies that have been linked to improved reliability (Larsen et al. 2015; Larsen et al. 2016; Larsen 2016a; Larsen 2016b).

All models considered show cumulative costs—through 2099—are higher under RCP 8.5 when compared to RCP 4.5, but that these differences do not begin accruing until after ~2060. We find that cumulative customer costs, through the middle of the century, are $1.52-$3.43 trillion ($2015; NPV) and $1.52-$3.42 trillion for RCP 4.5 and 8.5, respectively without aggressive undergrounding and O&M expenditures. By the end of the century, cumulative customer costs are $1.92-$5.57 trillion (RCP 4.5) and $1.92-$5.62 trillion (RCP 8.5) without aggressive undergrounding and O&M expenditures.

For the aggressive undergrounding and O&M expenditures scenario, cumulative customer costs, through the middle of the century, are $1.50-$2.51 trillion and $1.50-$2.51 trillion for RCP 4.5 and 8.5.

By the end of the century, cumulative customer costs are $1.95-$3.61 trillion (RCP 4.5) and $1.95-$3.63 trillion (RCP 8.5). This analysis suggests that some risk management practices—in the form of widespread and aggressive undergrounding of distribution lines and increased O&M spending—are not always cost-effective. This counter-intuitive finding occurs for the two models where the effect of the long-term reliability trend has been suppressed beyond 2005.

This analysis exposed a number of important topics for follow-on research. It was noted that the metrics to capture severe weather and utility T&D expenditures are imperfect and significant additional research is necessary. For example, it is likely that a metric that counts the annual number of days where peak wind speeds exceed some threshold (e.g., 35 mph) would more accurately account for changes in reliability. It is also important to conduct additional research into the cost of interruptions to different customer classes, including how risks may be distributed across different socio-economic populations. Evaluating the interruption costs to customers through an insurance perspective is an important new research angle worth exploring further (Mills and Jones 2016). And conducting a national interruption cost survey, using a consistent framework, would improve confidence in the assumptions about the value of reliability (LaCommare et al. 2017). Furthermore, little is known about the broader impacts to the economy from power system interruptions—especially the economic impact of interruptions that last longer than 16 hours. Sanstad (2016) shows that regional economic modeling is a "viable methodology for estimating large-scale costs of power disruptions, [but]…further development of regional economic models is needed to better capture the adaptive behavior of firms." Despite these research needs, this analysis provides initial insight into the range of potential costs to U.S. customers from power interruptions over the coming decades.

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Technical Appendix A: Detailed results for reliability regressions

This appendix contains more detailed information about how serial correlation and heteroscedasticity were addressed simultaneously. Also included are detailed results for the regressions and tests for stationarity.

Wooldridge (2002) indicates that it is common to preemptively correct standard errors for "arbitrary forms of serial correlation and heteroscedasticity…and that there are good reasons for this approach. First, the explanatory variables may not be strictly exogenous...[and] second, in most applications of generalized least squares, the errors are assumed to follow an AR(1) model". Zeileis (2004) also notes that econometric models typically contain autocorrelation and heteroscedasticity of "unknown form" and that it is extremely important to use simultaneous heteroskedastic and autocorrelation consistent (HAC) estimators prior to statistical inference. Interestingly, Baltagi et al. (2010) note that the "standard econometrics literature usually deals with heteroscedasticity ignoring serial correlation or vice versa". Accordingly, we correct the models' standard errors by assuming that there was both general serial correlation and heteroscedasticity. Prior to model interpretation, we applied the Newey and West (1994) procedure—using parameters specified in Stock and Watson (2002) —to correct for potential heteroscedasticity and/or serial correlation simultaneously.

The presence of non-stationary, time-series data in econometric models can lead to spurious regression results (Granger and Newbold, 1974). Therefore, it is critical to test for the presence of unit roots and address any issues related to non-stationarity, if present. There are at least two statistical tests available within the SAS software package to evaluate if unbalanced panel data underlying the models is stationary (SAS Institute, 2016). Tests that allow for the use of unbalanced panel include what are commonly known as "combination tests" (i.e., Fisher-type tests)—proposed by Maddala and Wu (1999) and Choi (2001). Choi (2001) found that the inverse normal test for unit roots generally performed better than other combination tests. For this reason, we test for the presence of unit roots using the inverse normal test. In this specific test, the null hypothesis is that the data is non-stationary (i.e., unit root is present). Conversely, the alternative hypothesis is that the data is stationary. It has been shown that the choice of lag length has important implications in tests for unit roots (e.g., see Ng and Perron 2001). Accordingly, the primary Augmented Dickey-Fuller (ADF) combination test procedure was set to select lag lengths according to a Modified Akaike Information Criterion as introduced by Ng and Perron (2001). The Phillips and Perron (1988) inverse normal statistics are also included, because this procedure is robust to general forms of heteroscedasticity and serial correlation. Table A-1 and Table A-2 show the results of the primary ADF and Phillips and Perron (1988) inverse normal unit root tests. In general, the results of these tests indicate, with strong statistical significance, that the data processes behind the models are stationary. It is important to note that the model specification, which includes both utility effects and a time trend (see row in italics within tables), is stationary and consistent with the model specification used in the interpretation of the final results. Table A-3 contains the reliability regression results used in models 1-4.

Table A-1. Unit root test results for SAIDI—with major events

Regression: *SAIDI (with major events)*	**ADF Inverse Normal Test**						**Phillips and Perron (1998) Inverse Normal Test**			
	Rho		**Tau**		**F**		**Rho**		**Tau**	
Deterministic Variables	**Z**	**Pr. < Z**	**Z**	**Pr. < Z**	**Z**	**Pr. < Z**	**Z**	**Pr. < Z**	**Z**	**Pr. < Z**
Zero Mean (independent of unit roots)	2.33	0.99	2.01	0.9776	N/A		2.68	0.9964	2.43	0.9925
Utility Effects	-10.86	<.0001	-8.3	<.0001	-6.48	<.0001	-7.96	<.0001	-7.54	<.0001
Utility Effects and Time Trend	*-7.82*	*<.0001*	*-6.32*	*<.0001*	*-4.67*	*<.0001*	*-6.26*	*<.0001*	*-6.27*	*<.0001*
Time Effects	-7.84	<.0001	-7.79	<.0001	N/A		-7	<.0001	-8.09	<.0001
Utility and Time Effects	-10.42	<.0001	-7.24	<.0001	-3.92	<.0001	-7.11	<.0001	-6.44	<.0001
Utility and Time Effects; Time Trend	-7.24	<.0001	-5.21	<.0001	-3.37	<.0001	-5.22	<.0001	-5.45	<.0001

Table A-2. Unit root test results for SAIFI—with major events

Regression: *SAIFI (with major events)*	**ADF Inverse Normal Test**						**Phillips and Perron (1998) Inverse Normal Test**			
	Rho		**Tau**		**F**		**Rho**		**Tau**	
Deterministic Variables	**Z**	**Pr. < Z**	**Z**	**Pr. < Z**	**Z**	**Pr. < Z**	**Z**	**Pr. < Z**	**Z**	**Pr. < Z**
Zero Mean (independent of unit roots)	-3.66	0.0001	-4.45	<.0001	N/A		-3.88	<.0001	-5.63	<.0001
Utility Effects	-9.51	<.0001	-7.21	<.0001	-4.8	<.0001	-7.79	<.0001	-7.28	<.0001
Utility Effects and Time Trend	*-7.77*	*<.0001*	*-6.15*	*<.0001*	*-5.68*	*<.0001*	*-6.82*	*<.0001*	*-7.22*	*<.0001*
Time Effects	-5.38	<.0001	-5.77	<.0001	N/A		-5.24	<.0001	-6.5	<.0001
Utility and Time Effects	-7.48	<.0001	-5.09	<.0001	-2.61	0.0045	-6.71	<.0001	-5.76	<.0001
Utility and Time Effects; Time Trend	-6.34	<.0001	-4.81	<.0001	-2.72	0.0033	-4.92	<.0001	-5.1	<.0001

Table A-3. Reliability regression results

	Dependent variable:		
Explanatory variables:	**Log of SAIFI (with major events; all weather)**	**Log of SAIFI (with major events)**	**Log of SAIDI (with major events)**
U.S. intercept	-17.70	-18.14	-101.15
Northwest region intercept	-17.90	-18.40	-100.92
Northern Great Plains region intercept	-17.82	-18.34	-101.49
Southwest region intercept	-17.62	-18.17	-101.40
Southern Great Plains region intercept	-17.90	-18.42	-101.44
Midwest region intercept	-17.82	-18.34	-101.00
Southeast region intercept	-17.75	-18.25	-100.74
Northeast region intercept	-17.30	-17.84	-101.34
Electricity delivered (MWh per customer)	0.031** (0.012)	0.03*** (0.011)	-0.01 (0.024)
Abnormally cold weather (% above average HDDs)	-0.001 (0.002)		
Abnormally warm weather (% above average CDDs)	0 (0.001)		
Abnormally high # of lightning strikes (% above average strikes)	0.001** (0.001)	0.001** (0.001)	0.001* (0.001)
Abnormally windy (% above average wind speed)	0.013 (0.012)	0.012 (0.012)	0.094*** (0.022)
Abnormally windy squared	-0.001 (0.001)	-0.001 (0.001)	-0.006*** (0.002)
Abnormally wet (% above average total precipitation)	0.002** (0.001)	0.003*** (0.001)	0.008*** (0.002)
Abnormally dry (% below average total precipitation)	0.002* (0.001)		
Outage management system?	0.091** (0.046)	0.088* (0.046)	0.235** (0.1)
Years since outage management system installation	0.005 (0.011)	0.004 (0.011)	0.007 (0.017)
Lagged T&D O&M expenditures ($2012 per customer)	-0.03 (0.089)	-0.033 (0.086)	-0.208 (0.206)
Number of customers per line mile	0 (0)	0 (0)	0 (0)
Share of underground T&D miles to total T&D miles	0 (0.002)	0 (0.002)	-0.008** (0.004)

	Dependent variable:		
Explanatory variables:	**Log of SAIFI (with major events; all weather)**	**Log of SAIFI (with major events)**	**Log of SAIDI (with major events)**
Year	0.009 (0.009)	0.009 (0.009)	0.053*** (0.014)
Degrees of freedom:	988	991	990
Number of utilities:	112	112	113
Adjusted R^2	0.53	0.53	0.53
Root mean square error	0.42	0.42	0.79
Utility effects:	Fixed	Fixed	Fixed

Notes:

(1) Standard errors are presented in parentheses underneath coefficient

(2) *** represents coefficients that are significant at the 1% level

(3) ** represents coefficients that are significant at the 5% level

(4) * represents coefficients that are significant at the 10% level

Technical Appendix B: Assumptions for ICE calculator

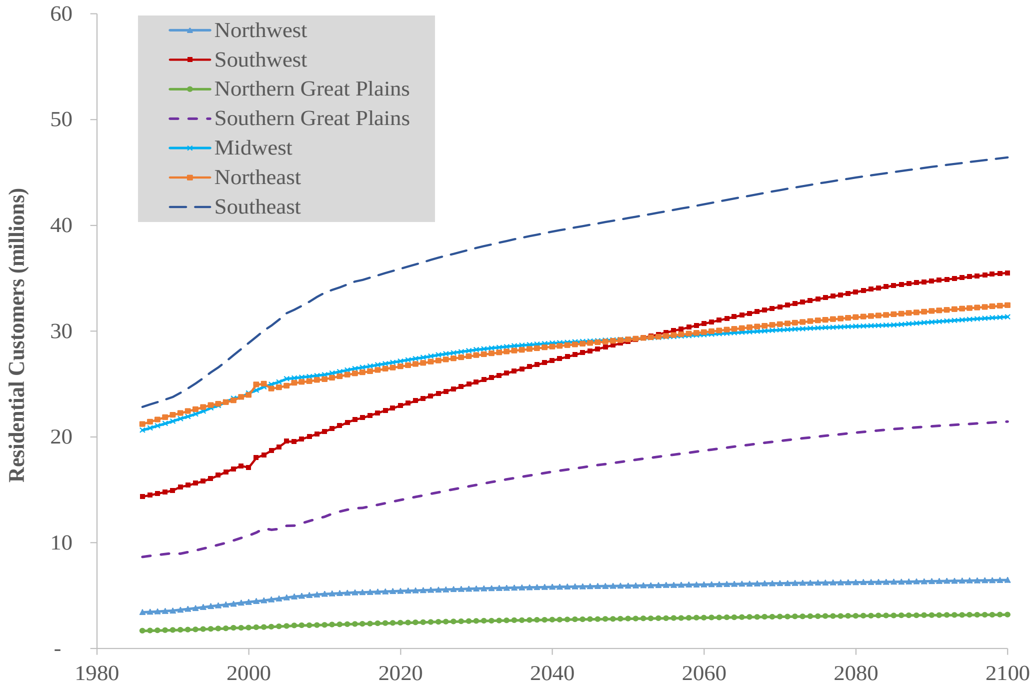

Figure B-1. Actual and projected number of residential customers by NCA region

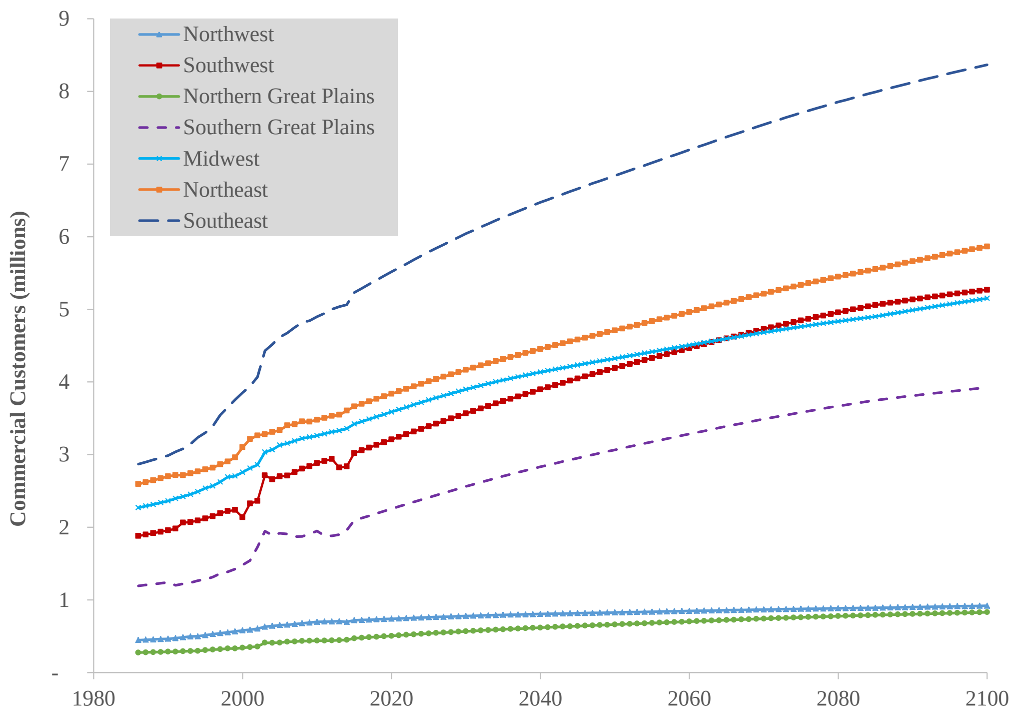

Figure B-2. Actual and projected number of commercial customers by NCA region

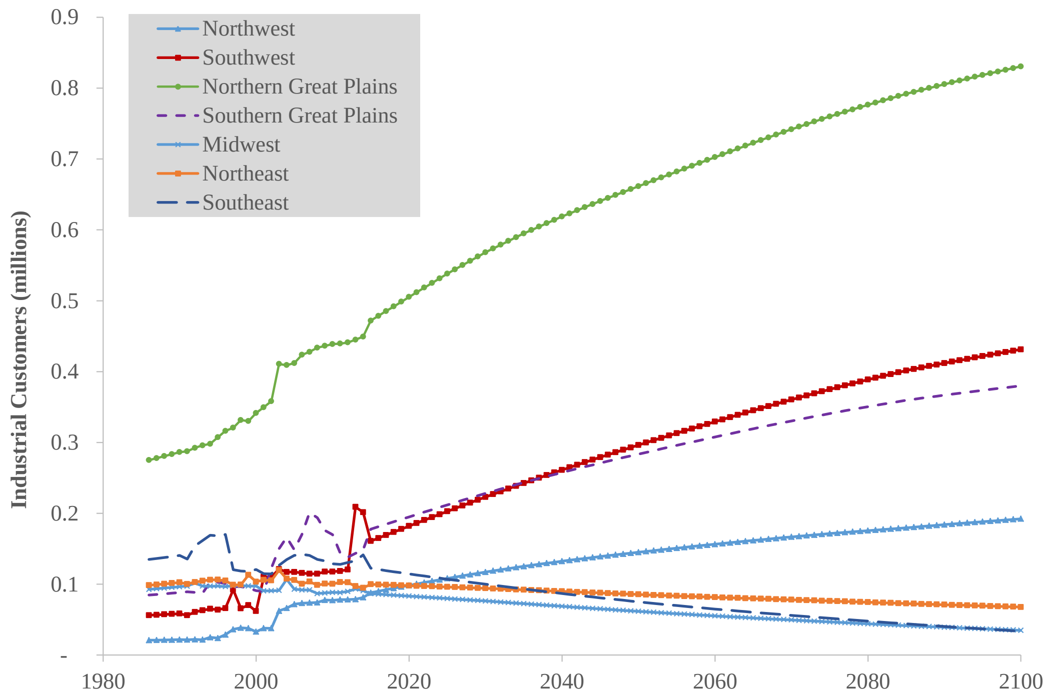

Figure B-3. Actual and projected number of industrial customers by NCA region

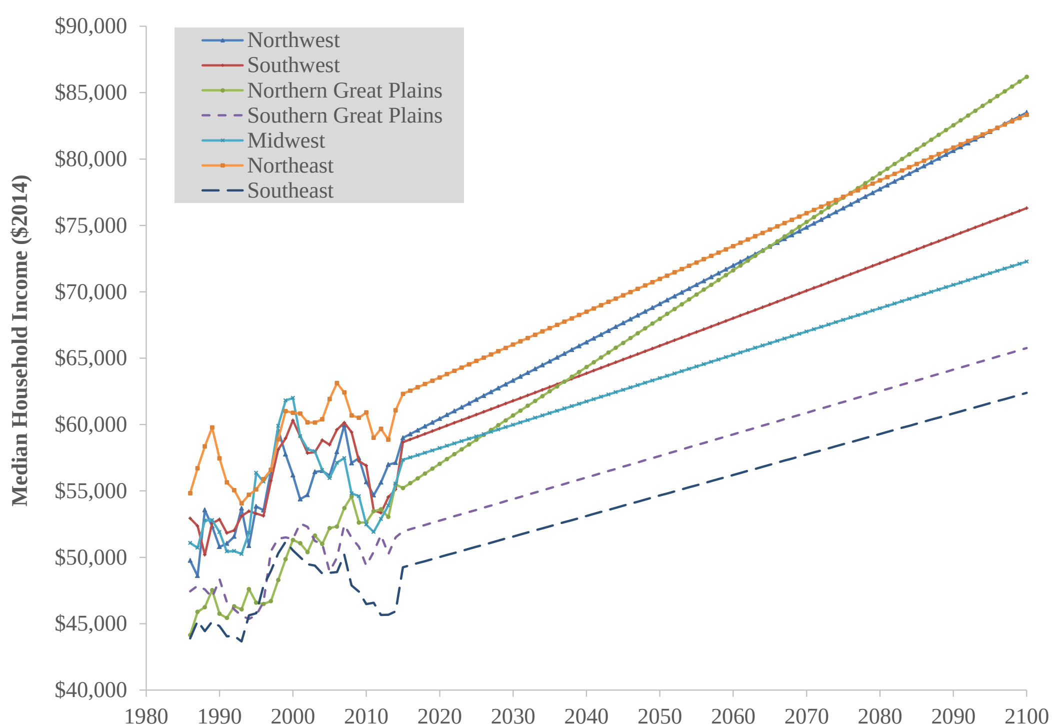

Figure B-4. Actual and projected household income by NCA region

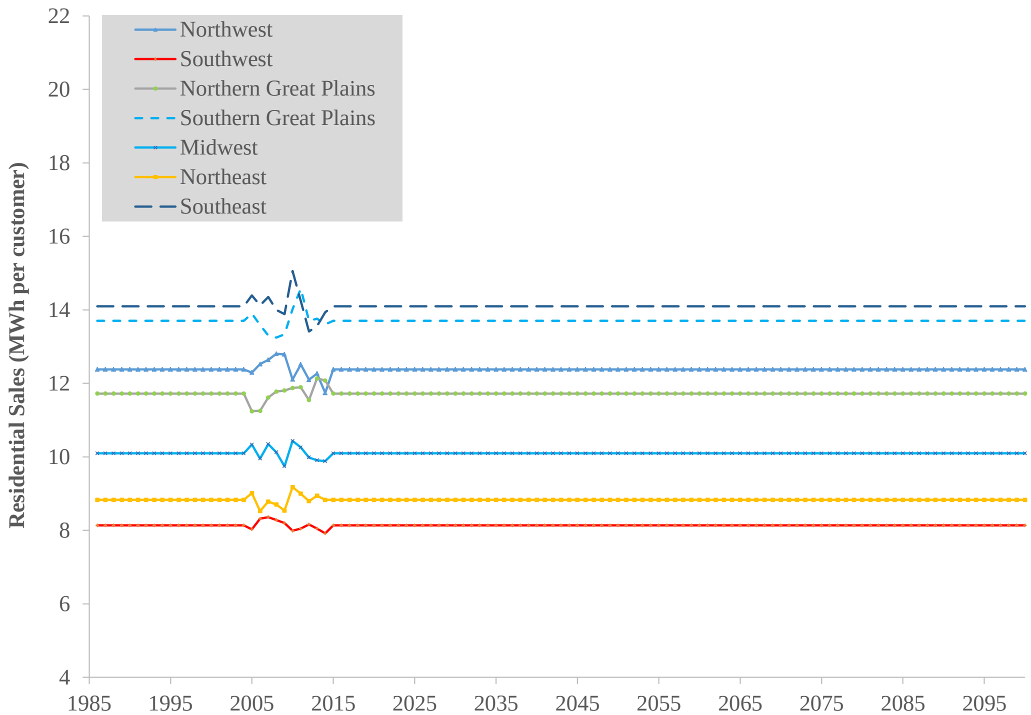

Figure B-5. Actual and projected residential sales per customer by NCA region

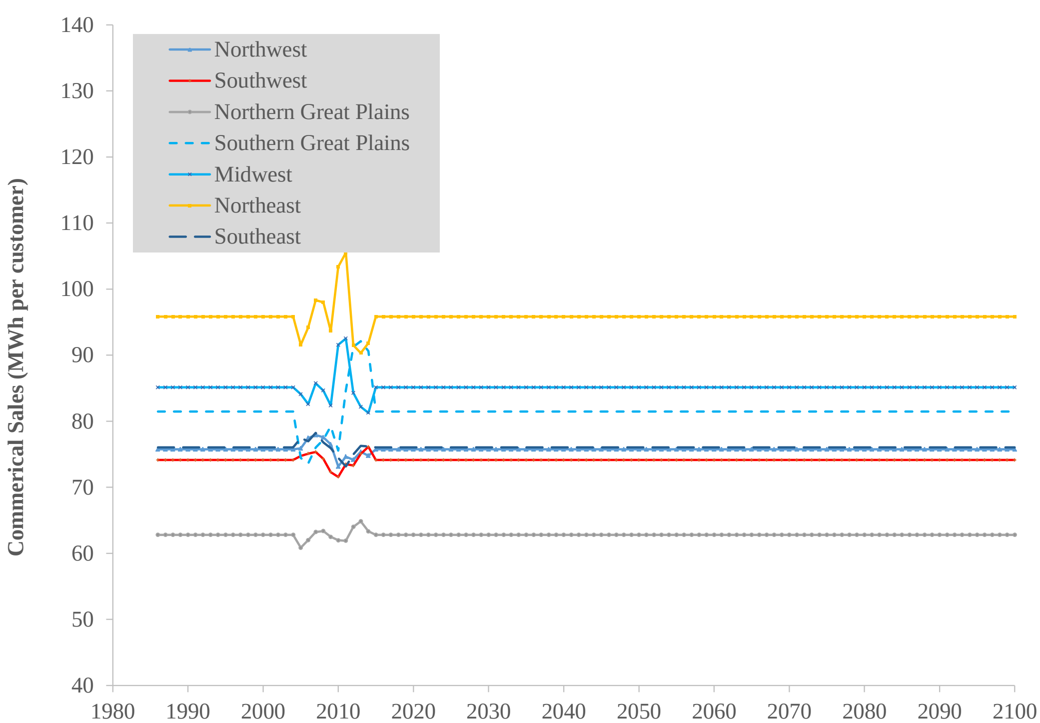

Figure B-6. Actual and projected commercial sales per customer by NCA region

Figure B-7. Actual and projected industrial sales per customer by NCA region

Technical Appendix C: Results for models 3 and 4

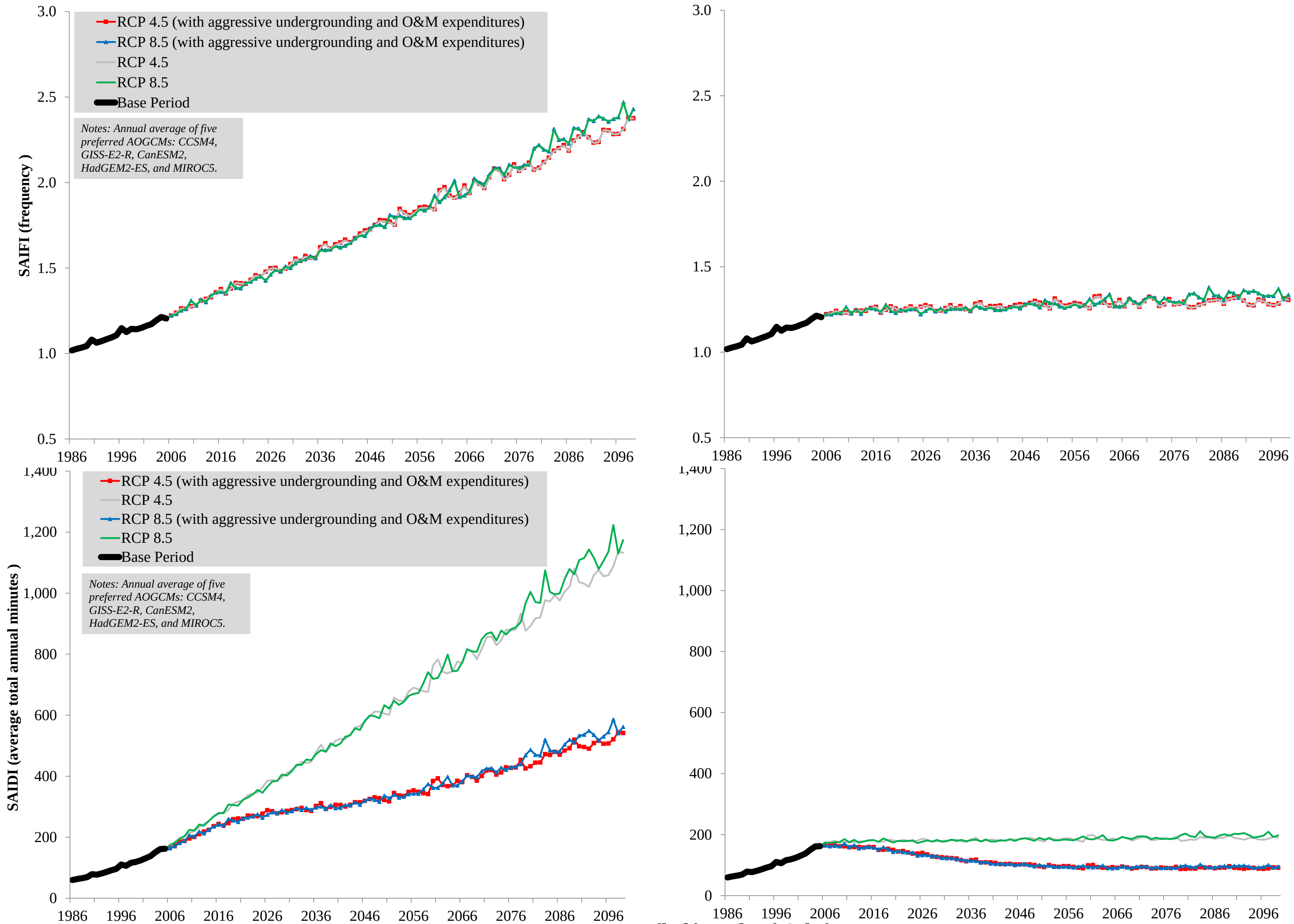

Figure C-1. Projected SAIFI (top) and SAIDI (bottom) for models 3 (left) and 4 (right)

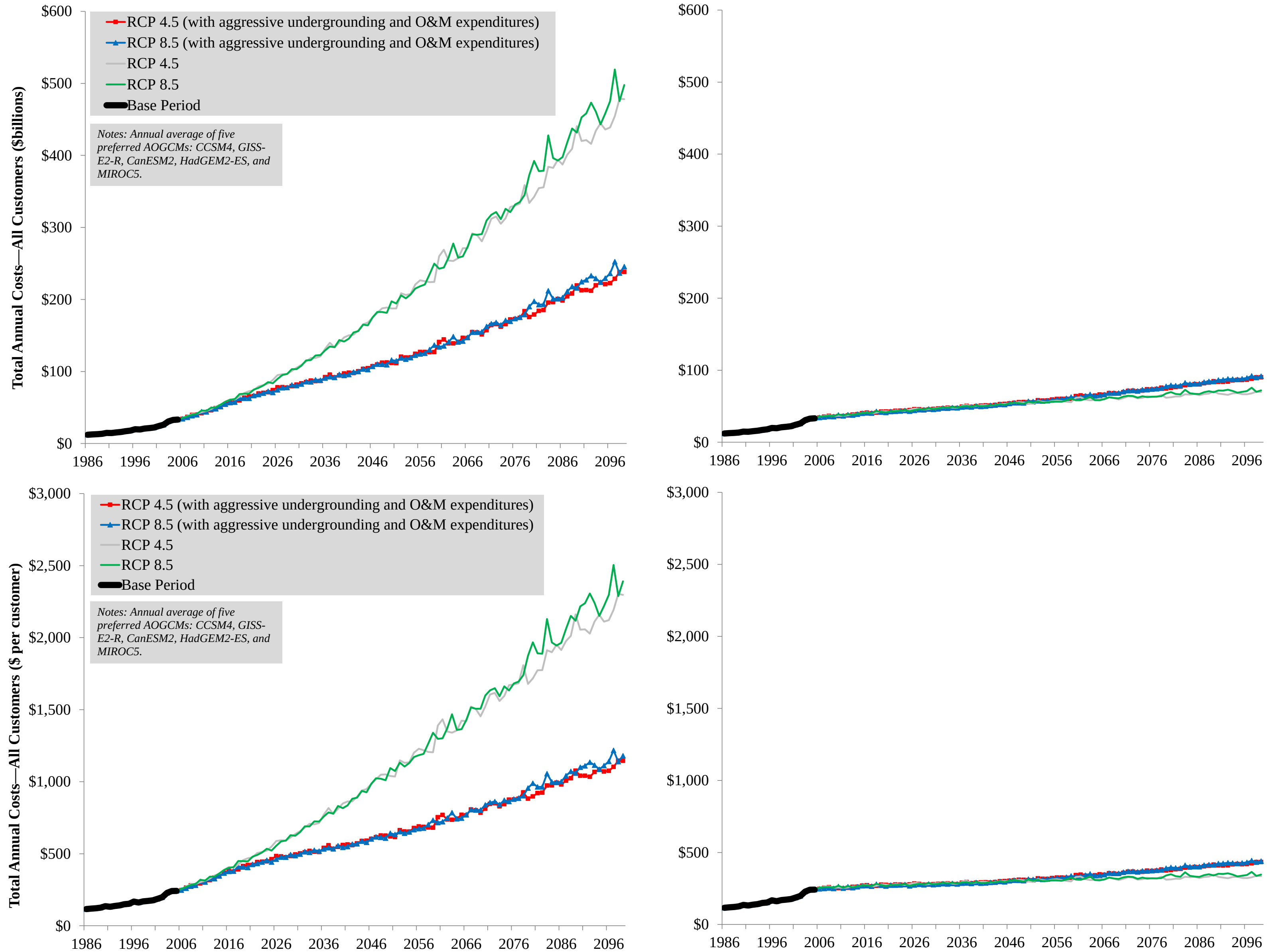

Figure C-2. Projected annual costs (top) and costs per customer (bottom) for models 3 (left) and 4 (right)

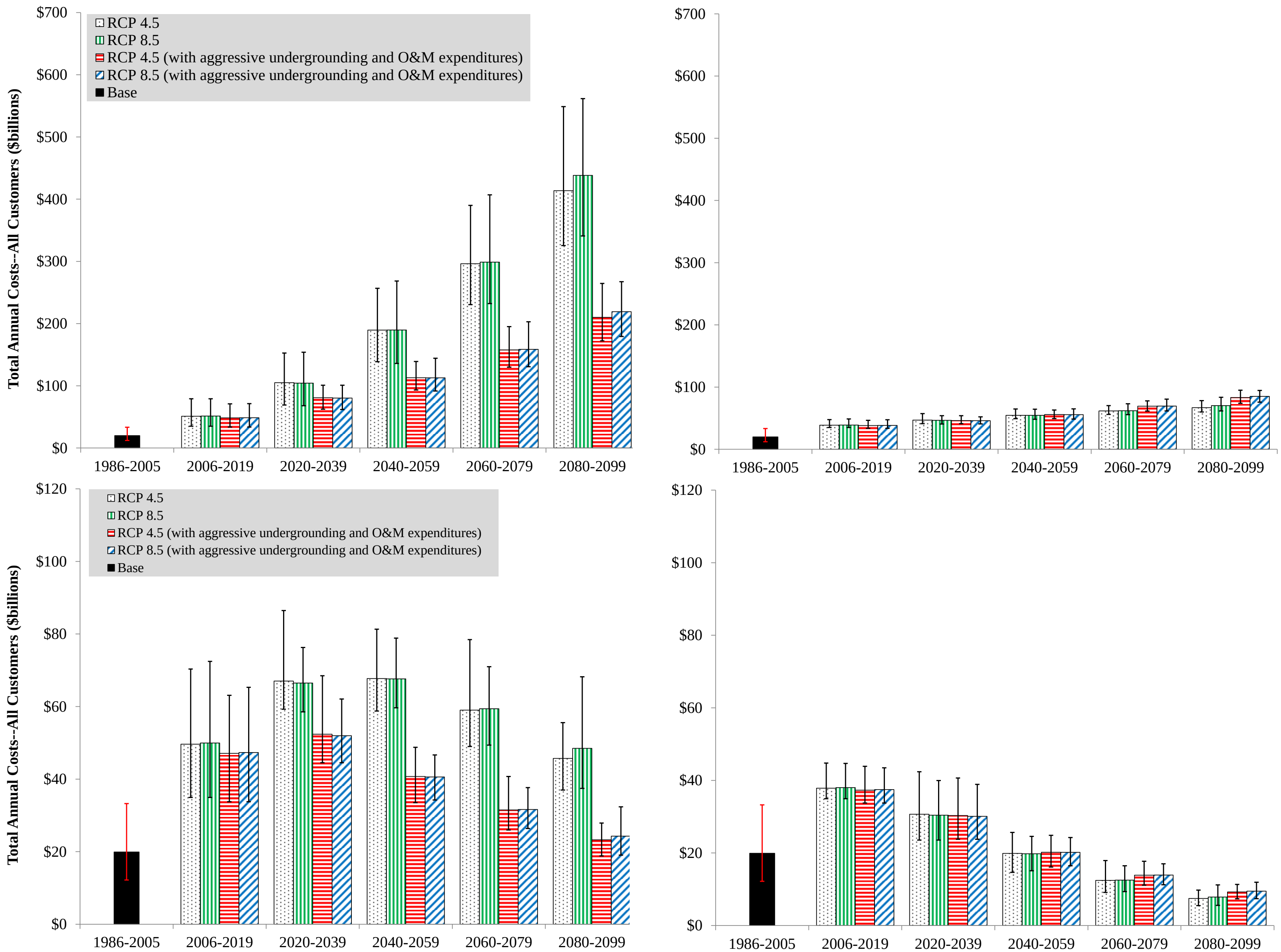

Figure C-3. Annual costs by era (not discounted; top) and annual costs by era (discounted 3%; bottom) for models 3 (left) and 4 (right)

Table C-1. Cumulative costs for model 3 through middle and end-of-century—without and with aggressive undergrounding and O&M expenditures

Model 3	***2015-2059***				***2015-2099***			
	Without aggressive undergrounding and O&M expenditures		***With aggressive undergrounding and O&M expenditures***		***Without aggressive undergrounding and O&M expenditures***		***With aggressive undergrounding and O&M expenditures***	
Metric (trillions of $2015)	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Cumulative Costs	$6.60↑	$6.60	$4.55	$4.54	$20.80	$21.34	$11.90	$12.10
NPV Cumulative Costs	$3.39	$3.38	$2.52	$2.51	$5.48	$5.54	$3.62	$3.63

Table C-2. Cumulative costs for model 4 through middle and end-of-century—without and with aggressive undergrounding and O&M expenditures

Model 4	***2015-2059***				***2015-2099***			
	Without aggressive undergrounding and O&M expenditures		***With aggressive undergrounding and O&M expenditures***		***Without aggressive undergrounding and O&M expenditures***		***With aggressive undergrounding and O&M expenditures***	
Metric (trillions of $2015)	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Cumulative Costs	$2.57	$2.56	$2.57↑	$2.57	$5.14	$5.21	$5.62	$5.66
NPV Cumulative Costs	$1.54↑	$1.54	$1.53↑	$1.53	$1.94	$1.94↑	$2.00	$2.00↑