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Assessing the Near-Term Risk of Climate Uncertainty: Interdependencies among the U.S. States

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Assessing the Near-Term Risk of Climate Uncertainty: Interdependencies among the U.S. States

George Backus,[*] Thomas Lowry,[†] Drake Warren,[‡] Mark Ehlen,[‡] Geoffrey Klise,[†] Verne Loose,[‡] Len Malczynski,[†] Rhonda Reinert,[⊥] Kevin Stamber,[ǂ] Vince Tidwell,[†] Vanessa Vargas,[‡] and Aldo Zagonel[ǁ]

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Abstract

Policy makers will most likely need to make decisions about climate policy before climate scientists have resolved all relevant uncertainties about the impacts of climate change. This study demonstrates a risk-assessment methodology for evaluating uncertain future climatic conditions. We estimate the impacts from responses to climate change on U.S. state- and national-level economic activity from 2010 to 2050. To understand the implications of uncertainty on risk and to provide a near-term rationale for policy interventions to mitigate the course of climate change, we focus on precipitation, one of the most uncertain aspects of future climate change. We use results of the climate-model ensemble from the Intergovernmental Panel on Climate Change's (IPCC) Fourth Assessment Report (AR4) as a proxy for representing climate uncertainty over the next 40 years, map the simulated weather from the climate models hydrologically to the county level to determine the physical consequences on economic activity at the state level, and perform a detailed 70-industry analysis of economic impacts among the interacting lower-48 states. We determine the industry-level contribution to the gross domestic product and employment impacts at the state level, as well as interstate population migration, effects on personal income, and consequences for the U.S. trade balance. We show that the mean or average risk of damage to the U.S. economy from climate change, at the national level, is on the order of $1 trillion over the next 40 years, with losses in employment equivalent to nearly 7 million full-time jobs.

Acknowledgments

This study was performed under the Laboratory-Directed Research and Development (LDRD) program at Sandia National Laboratories (Project 138735), and we gratefully thank the Sandia LDRD program for its financial support of this study. We acknowledge the additional expert efforts of the following colleagues at Sandia: Tim Trucano, David Robinson, Arnie Baker, Brian Adams, Elizabeth Richards, John Siirola, Mark Boslough, Mark Taylor, Ray Finely, Lillian Snyder, Dan Horschel, Andjelka Kelic, Jesse Roach, Marissa Reno, William Stubblefield, Laura Swiler, Laura Cutler, Anna Weddington, William Fogelman, Jim Strickland, John Mitchiner, Howard Hirano, and James Peery. Contributions by Dr. James P. Smith with the Computer and Computational Sciences Group at Los Alamos National Laboratory (LANL), by Dr. David Higdon with the Statistical Sciences Group at LANL, and by Dr. Joe Galewsky from the Department of Earth & Planetary Sciences at the University of New Mexico are also greatly appreciated. In addition, we are grateful to the following reviewers for their insightful comments and suggestions: Dr. Terry Barker, Director, Cambridge Centre for Climate Change Mitigation Research, Department of Land Economy, Cambridge University; Dr. Chris Hope, Energy and Environment Research Group, Judge Business School, Cambridge University; Dr. Robert Harriss, President and CEO of the Houston Advanced Research Center and former Director of the Institute for the Study of Society and the Environment at the National Center for Atmospheric Research; Dr. Michael Mastrandrea in the Center for Environmental Science and Policy at Stanford University; Dr. Elizabeth Stanton at the Global Development and Environment Institute at Tufts University and the Stockholm Environment Institute; and Dr. Jonathan Overpeck, Co-Director in the Institute of the Environment and professor in the Geosciences and Atmospheric Sciences departments at the University of Arizona.

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What we anticipate seldom occurs; what we least expect generally happens.

Benjamin Disraeli, British prime minister (Disraeli 1891)

We know we cannot wait for certainty. Failure to act because a warning isn't precise enough is unacceptable. . . . if we wait, we might wait too long.

General Gordon R. Sullivan, USA (Ret.)
Former Chief of Staff, U.S. Army (CNA 2007)

Executive Summary

The uncertainty in climate change and in its impacts is of great concern to the international community. While the ever-growing body of scientific evidence substantiates present climate change, the driving concern about this issue lies in the consequences it poses to humanity. By the time the negative impacts of climate change significantly affect populations, it will be too late to prevent the escalating damage. The greenhouse gases that dominate the warming process, especially carbon dioxide (CO_2), will produce enduring impacts for over a millennium (Solomon et al. 2009). Should the extent of climate change cross a threshold where geophysical processes reinforce manmade climate change, the long-term consequences could be catastrophic (Keller et al. 2008). However, in this study we confine ourselves to the near-term risk of climate change through the year 2050, and we do not consider the long-term risk of catastrophic climate change.

In this study, we quantify the risk from uncertain climate change to each of the interacting U.S. states, noting the impact on the population and businesses as they respond to changing climatic conditions. Largely, it is the uncertainty associated with climate change and its impacts that presents the greatest problem for policy makers. If society knew how climate change would exactly unfold, it could readily determine what adaptation and mitigation responses should be undertaken. However, decades of climate science research indicate that it may not be possible to obtain a definitive reduction in the uncertainty, and certainly not possible within the time frame that is needed to counter the worst effects of climate change (Roe and Baker 2007). While current best estimates of global warming by the year 2100 forecast a rise in the global mean (average) temperature on the order of 2º to 4ºC, the uncertainty of these estimates is relatively large. Various studies have attempted to define this uncertainty, which has been characterized as the "long tail" (Hegerl et al. 2007) in statistical terms. Fundamentally, the long tail suggests that the future global temperature may be higher than projected best estimates.

The analyses by the Intergovernmental Panel on Climate Change (IPCC) and the ensemble of model results provided by these analyses are currently the generally recognized statement on the future of climate change. The variation or differences in results among the climate models used for the IPCC Fourth Assessment Report (AR4) embodies the uncertainty most associated with climate forecasts. In this study, we use the results of the AR4 ensemble of climate simulations as a proxy for representing climate uncertainty over the next 40 years. We apply this uncertainty to consider the risk of uncertain precipitation conditions as it applies to individual U.S. states as well as the nation. We select precipitation because it more directly affects economic activities and is more uncertain, which implies more risk, than the commonly used considerations related to temperature (Trenberth 2008; Allen and Ingram 2002; NAST 2001). In climate studies, temperature is the common attribute used to estimate the impacts of climate change.

Uncertainty and Risk

The impacts from climate change are largely negative (IPCC 2007b). From a policy perspective, the incentive to act comes by comparing the risk (cost) of inaction with the cost of action to successfully mitigate climate change. Risk is often characterized in terms of probability and consequence. There is a spectrum of conditions (or events) involved with climate change for assessing risk. At one end of the spectrum are those conditions that may occur frequently (high probability) and result in minimal damage (low consequence). An example of a high-probability, low-consequence type of event would be excessive rainfall that results in damage to the roof of your house. At the other end of the spectrum are conditions that do not occur frequently (low probability) but may be life changing or catastrophic (high consequence) if they do occur. Examples of low-probability, high-consequence types of risks would be a prolonged severe drought in an area and, at the very extreme, an asteroid collision with Earth.

The less we understand about climate change, the larger the tail on the uncertainty distribution for climate change becomes. Greater extremes in climatic conditions imply greater societal consequences should those extremes occur. Accordingly, the greater the uncertainty is, the greater is the risk. For example, taking a commercial flight on Virgin Galactic's SpaceShipTwo spacecraft is considered to have a relatively high risk because of a lack of information about its reliability. Risk derives and increases from "not knowing." The efforts of those skeptical of climate-change projections to demonstrate limitations in the accuracy of climate-change analyses may cause climate scientists to change the priorities of their research, but the real effect of emphasizing limitations is to accentuate the level of uncertainty in future climatic conditions. Rather than justifying a lack of response to climate change, the emphasis on the uncertainty enlarges the risk and reinforces the responsibility for pursuing successful long-term mitigation policy. If those skeptical of climate change want to halt government initiatives in climate policy, they must act to reduce the uncertainty and demonstrate that the future climatic conditions will remain below dangerous levels. See Mastrandrea and Schneider (2004) for a discussion on the potential for dangerous climate change.

The consequence of adverse conditions is often framed in economic terms, such as the monetary value of a loss or the number of jobs lost. And because human behavior is so complex, there is even greater uncertainty in the prediction of future economic conditions than there is in the prediction of climate change alone. Yet, despite uncertainty about the future, cost-benefit analyses are conducted on a daily basis as aids for policy makers on issues of critical importance to the nation such as health care, social security, and defense. Similarly, individuals weigh the costs and benefits of taking certain actions, like purchasing insurance, to minimize risk for themselves and their families.

We use computer models to predict the near-term impacts of climate change on state-level economies from 2010 through 2050 because, in the absence of quantifying the near-term cost, the need to address climate change seems more remote and has a diluted sense of urgency. The forecasts from the economic models we applied will almost certainly be highly inaccurate, but this approach is the only coherent option available to inform current decision making. An imprecise prediction can be useful for comparing options to address a significant problem if we assume that such a prediction adequately defines the future relative to the choices to be made and, more importantly, represents a mutually agreed upon basis from which stakeholders can debate alternatives on common ground. This same reasoning applies to climate change. While better science could reduce some of the uncertainty, this reduction will occur after the time frame for effective contemporary policy action. The IPCC climate projections (IPCC 2007c), along with any limitations and nuanced caveats associated with their usage, represent the best and the most visible climate-science reference for timely framing of the national and international assessment of climate-change risk.

Analysis Design and Process

All analyses in this study correspond to the IPCC Special Report on Emissions Scenarios (SRES) A1B scenario. The IPCC considers the A1B to be a “balanced” scenario of economic growth with expanding renewable energy use. We have not addressed variation in CO_2 emissions or mitigation efforts to reduce emissions. Figure 1 presents an overview of the three major steps in our analysis process. We start with the existing ensemble of the IPCC Program for Climate Model Diagnosis and Intercomparison (PCMDI) computer runs, as depicted in the left-hand box. Specifically, we use the PCMDI data set representing the A1B scenario and containing the precipitation data (Leroy et al. 2008) produced by 53 runs of 24 of the currently most accepted climate models. We use results from these runs to create a proxy probability distribution of potential climatic futures for precipitation and temperature conditions between 2010 and 2050. The interrelated volatility of both temperature and precipitation are included as part of the ensemble results and used in the analysis, but it is principally the uncertainty in precipitation that permeates the analysis. Next, using the Sandia hydrological model, we map the temperature and precipitation data to the county and state levels in the continental United States to determine the availability of water for selected industries within each state, as represented in the middle box. During the third step, noted in the right-hand box, we employ the Regional Economic Models Incorporated (REMI) macroeconomic model (REMI 2009) to determine the cost of adjusting water usage to match water availability and calculate the macroeconomic impacts resulting from revisions in the comparative economic advantage of each state.

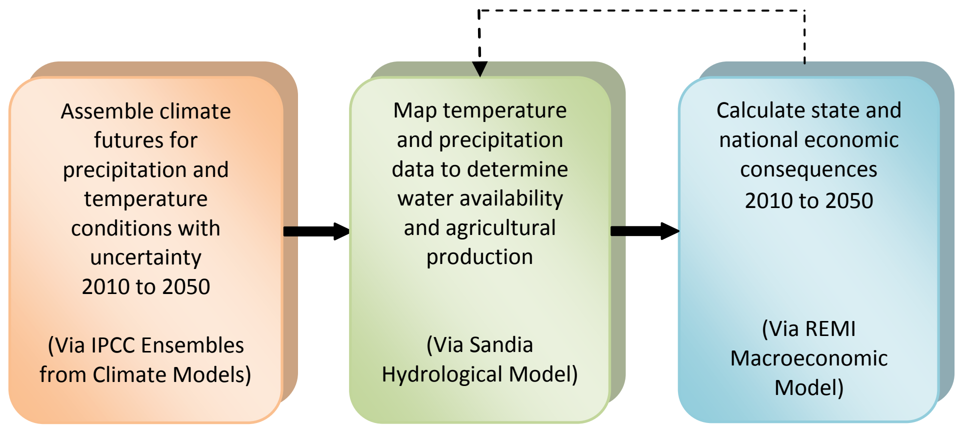

Figure 1. Analysis process.

We specifically analyze how consumers and industries respond (adjust) to the changing economic and physical conditions created by climate change. These responses attempt to lessen the economic impacts that would otherwise occur, and thus any integrated economic assessment needs to incorporate the actions that people take to compensate for negative events. The methodology underlying our analysis, which is implemented through the REMI model, is based on historical response patterns of industries and consumers—how real people in business and on a personal level have behaved in the past to changing economic conditions, policies, and events. We believe that using historical real-world behaviors is a more realistic approach than simulating the choices people make based on the commonly used economic assumptions of optimality and perfect knowledge of future conditions (Manne et al. 1995; Nordhaus and Yang 1996; Ackerman and Nadal 2004).

Economic studies often apply discount rates in their calculations of future costs either to (1) better accommodate adverse situations in the future based on the assumption that people will have greater access to resources in the future or (2) recognize that adversity in the present has a greater impact on human decision making than those threats that are still in a distant future. Essentially, a discount rate greater than zero percent (0%) places a lower value on money in the future than on money in the present. Because of the current controversy surrounding the use of different discount rates to assess the economic impacts of climate change, this study estimates the impacts using three discount rates: 0% per year, 1.5% per year, and 3.0% per year. The 1.5% rate roughly corresponds to the discount rate used in the Stern Review (Stern 2007). Other authors make a strong case for a 0% rate (Dasgupta et al. 1999; Posner 2004), whereas the 3% rate more closely conforms to historical orthodoxy (or conventional practice) in economic analyses (EPA 2000; OMB 2008). Because this study considers the costs to the economy from the perspective of those experiencing the impacts at a future time, and because there is no attempt to define mitigation or other policies in the present that would limit those impacts, we use the 0% discount rate as a point of neutrality. We thus are simply reporting the predicted future costs of climate change in the accounting sense. How the society determines the present values of those costs from a liability or preference perspective falls in the conventional realm of financial or social discounting—

appropriately using discount rates in excess of zero. Note that the values presented in some of the tables and figures reflect only the 0% discount rate. This approach has been taken to conserve space, and data on all three rates are generally available in our complete report.

We use precipitation, one of the most uncertain outputs from climate models, as the variable to characterize the primary uncertainty linking temperature and the frequency and intensity of future atmospheric conditions. Adjusting to the higher temperatures associated with climate change would not seem overwhelming if the United States had an inexhaustible supply of abundant clean energy and plenty of water. Air conditioning could, for example, be used within enclosed living spaces and work spaces for more months during the year than it is currently used, and the economic impacts would be manageable. At the other extreme, however, attempts to accommodate higher temperatures when there is no water available (for industry, people, or the energy sources that serve them) would produce severe economic impacts for the United States. We note that within the 40-year time frame addressed in this study, there is a diminishingly small probability that an impact on that scale would occur. However, to adequately assess the economic impacts of climate change, we need to consider the full range of possibilities of precipitation—from plenty of water to no water.

Analysis Results

Below we present some significant results from the analysis, including impacts on the U.S. GDP, employment, and industry. The analysis uses the concept of exceedance probabilities to describe the various levels of uncertainty. To generate the results, we simulate future conditions using the computer models and process noted in Figure 1 across the full range of exceedance probabilities. The range of exceedance probabilities extends from 100% (the maximum realizable precipitation) to 0% (the minimum realizable precipitation). An exceedance probability measures the likelihood (or chance) a particular consequence of climate change will exceed (be greater than) the value reported for that probability. For example, a 25% exceedance probability means there is an estimated 25% chance an impact will exceed the indicated value (for example, in dollars of lost GDP) associated with that percentage of impact. The body of the full report for this study provides a detailed discussion of the analysis process and a thorough explanation of the results.

Figure 2 shows the estimated reduction in the U.S. GDP over the period 2010 to 2050 at various levels of uncertainty based on calculations for a 0% discount rate. The values on the solid red line represent the total cost over the 40-year period. These values are considered the “best estimates” in our analysis. The extreme risk is the possibility of losing most of the economy.

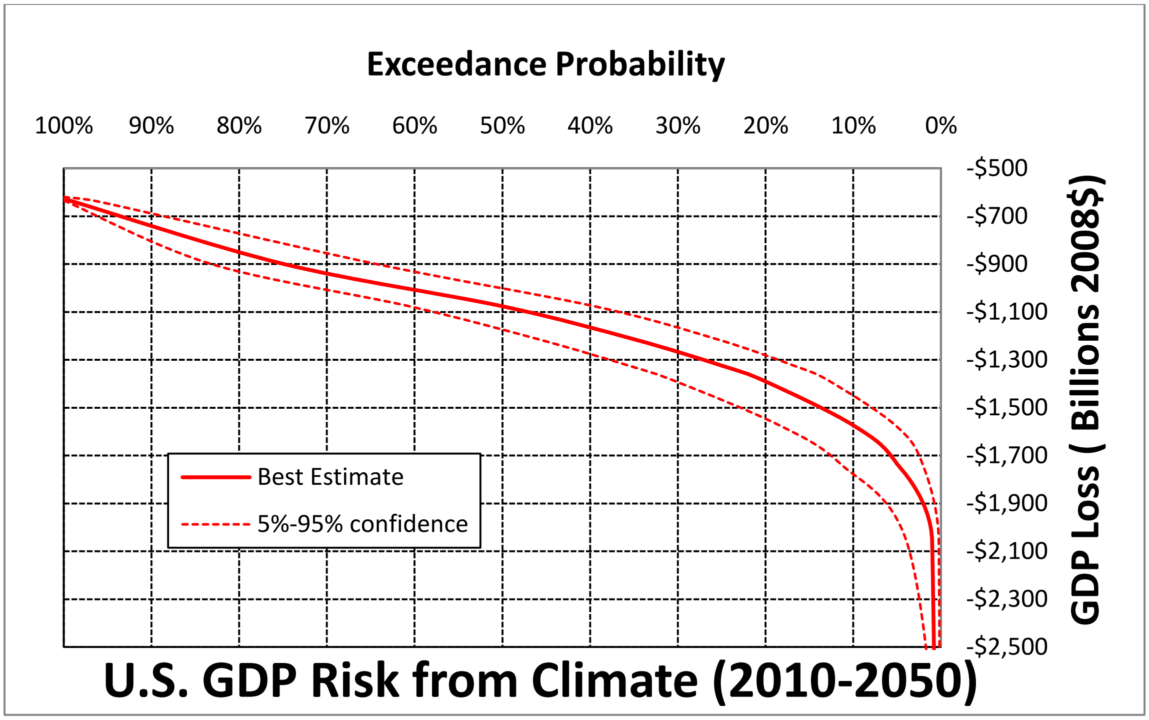

Figure 2. U.S. GDP impacts (2010–2050) for a 0% discount rate.

The dashed lines in Figure 2 are important because they characterize our knowledge of the uncertainty of the best-estimate values to within 90% confidence, reflecting a lower and an upper limit on the uncertainty, from 5% (lower dashed line) to 95% (upper dashed line). Effectively, the dashed lines represent the uncertainty of the best-estimate exceedance-probability values. In other words, for any given point on the best-estimate line, it is highly likely that the impact will lie somewhere between the corresponding values on the enveloping dashed lines.

Our study generates U.S. GDP impacts in 2050 that are comparable to the impacts determined in the Stern Review (Stern 2007) and in its associated studies (Ackerman et al. (2009). The Stern Review, however, includes noneconomic losses that are not contained in our study. Mendelsohn et al. (2000) considered global impacts that include the United States as a studied region, but these researchers derived a positive impact on the GDP within the 2050 time frame. Previous analyses, including the Stern Review, have relatively simple damage functions that primarily capture only the direct impacts. The use of combined industry-level econometric and input-output methods, as applied in our study, highlights the effects of economic multipliers that capture added indirect impacts as damages flow through the economy to suppliers and employees. Importantly, the indirect impacts are typically two to five times larger than the direct impacts.

Table 1 shows the values associated with the "best estimate" line in Figure 2 above at the three discount rates. Also included for each rate is the value for the summary (or total) risk. The total risk of climate change is approximately the sum of the consequence associated with each of the exceedance probabilities, from 100% to 0%, for all events considered in the study. These probabilities cover the full range of uncertainty. Note that the analysis only considers the impact of reduced precipitation. Even if there was abundant water on average, forecasts of climate change still have a trend toward reduced precipitation that includes both drought and flood conditions. We do not include the cost of flooding in the assessment. Flooding is easier to accommodate than drought, with lesser costs, and is the subject of other studies (McKinsey 2009).

Table 1. GDP Impacts and Summary Risk (2010–2050)

Change in National GDP (Billions of 2008$)										
Discount rate	Exceedance Probability									Summary Risk
	99%	75%	50%	35%	25%	20%	10%	5%	1%	
0.0%	-$638.5	-$899.4	-$1,076.8	-$1,214.5	-$1,324.6	-$1,390.8	-$1,573.9	-$1,735.4	-$2,058.5	-$1,204.8
1.5%	-$432.0	-$595.9	-$707.4	-$795.0	-$865.1	-$907.2	-$1,024.6	-$1,129.3	-$1,340.2	-$790.3
3.0%	-$301.9	-$407.4	-$479.4	-$536.6	-$582.4	-$610.0	-$687.2	-$756.8	-$898.2	-$534.5

The total estimated (average) loss to the GDP, the summary risk, due to climate change is approximately $1.2 trillion through 2050 at a 0% discount rate.[1] For the same discount rate, the forecast *annual* loss to the GDP by 2050 at the 50% exceedance probability could exceed $60 billion per year and could exceed $130 billion per year at the 1% exceedance probability. The summary loss is 0.2% of the cumulative GDP. Casting a $1.2 trillion impact, as we have calculated in this study for the loss in the GDP at a 0% discount rate, in the context of a relatively small percentage of total economic activity over the time period distorts the actual implications for those who locally experience the loss. Further, when taken in isolation, the value can give a false comfort in disregarding post-2050 impacts. The impacts increase rapidly in the end years of our analysis. If we had continued our analyses further into the future, the reported cost would be much larger than the 2050 cost we have estimated.

Figure 3 shows the impacts on employment measured in lost labor years from 2010 to 2050 at various levels of uncertainty for a 0% discount rate. A labor year is equivalent to having one full-time job for a year.

[1] All costs are presented in 2008 U.S. dollars.

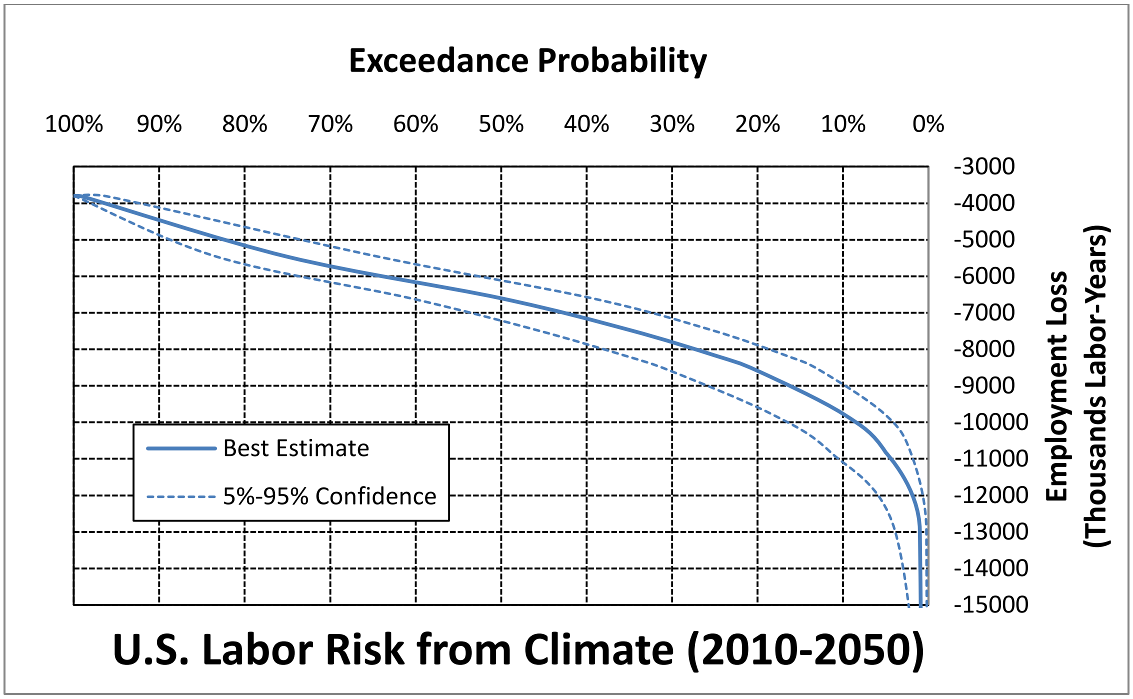

Figure 3. U.S. employment impacts (2010–2050) for a 0% discount rate.

Table 2 shows the employment-loss values associated with the best-estimate (solid blue) line in Figure 3 at a 0% discount rate. The total risk is nearly 7 million lost labor years due to climate change. The annual job loss by 2050 at the 50% exceedance probability is nearly 320,000 full-time jobs. At the 1% exceedance probability by 2050, the annual job loss rises to nearly 700,000 full-time jobs. Note that these latter job statistics have been taken from the data and are not included in Figure 3.

Table 2. Employment Impacts and Summary Risk (2010–2050)

Change in Employment (Thousands)									
Exceedance Probability									Summary Risk
99%	75%	50%	35%	25%	20%	10%	5%	1%	
-3,815	-5,463	-6,601	-7,468	-8,166	-8,587	-9,764	-10,819	-12,961	-6,863

When water availability limits economic production within the United States, one alternative is to import the lost commodities, especially food. Figure 4 shows the impact of climate change on the U.S. trade balance for the 40-year period. This study is U.S. centric and assumes that the rest of the world is unaffected by climate change and can accommodate additional U.S. demands for imports. Climate change may improve agriculture and the core industries of Canada and Russia, but a recent study by Nelson et al. (2009) indicates the costs of agricultural products will rise throughout the rest of the world. Figure 4 is assuredly inaccurate, but it does exemplify how climate change can affect trade balances.

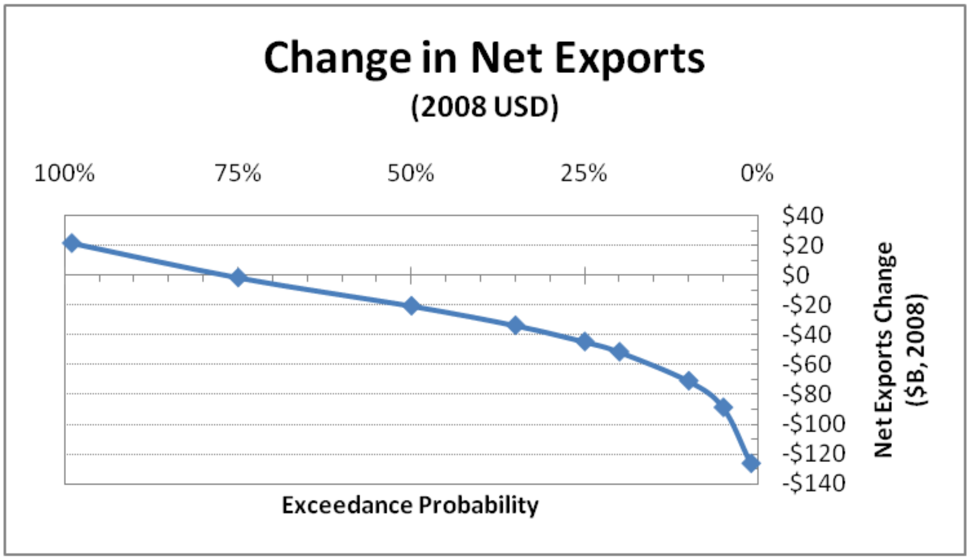

Figure 4. Trade-balance impacts (2010–2050).

The downward trend in Figure 4 indicates that the United States has to import increasing amounts of goods and services, most of which is food. For example, there is a 50% chance that the United States would need to import more than $20 billion in goods and services as a result of climate change over the 40-year period. Assuming that the rest of the world can accommodate increased U.S. demands, the annual trade balance by 2050 increases by an additional $0.5 billion per year at the 50% exceedance probability and by an additional $8 billion per year at the 1% exceedance probability.

Because climate change is predicted to increase the volatility of temperature and precipitation, the estimated impacts over time also show volatility. Figure 5 illustrates the annual impacts on the national GDP as a function of varying exceedance probabilities for reduced water availability, as stated in the legend of the graph. As shown, greater losses are evident in succeeding years, and the lower exceedance probabilities are associated with greater impacts on the GDP.

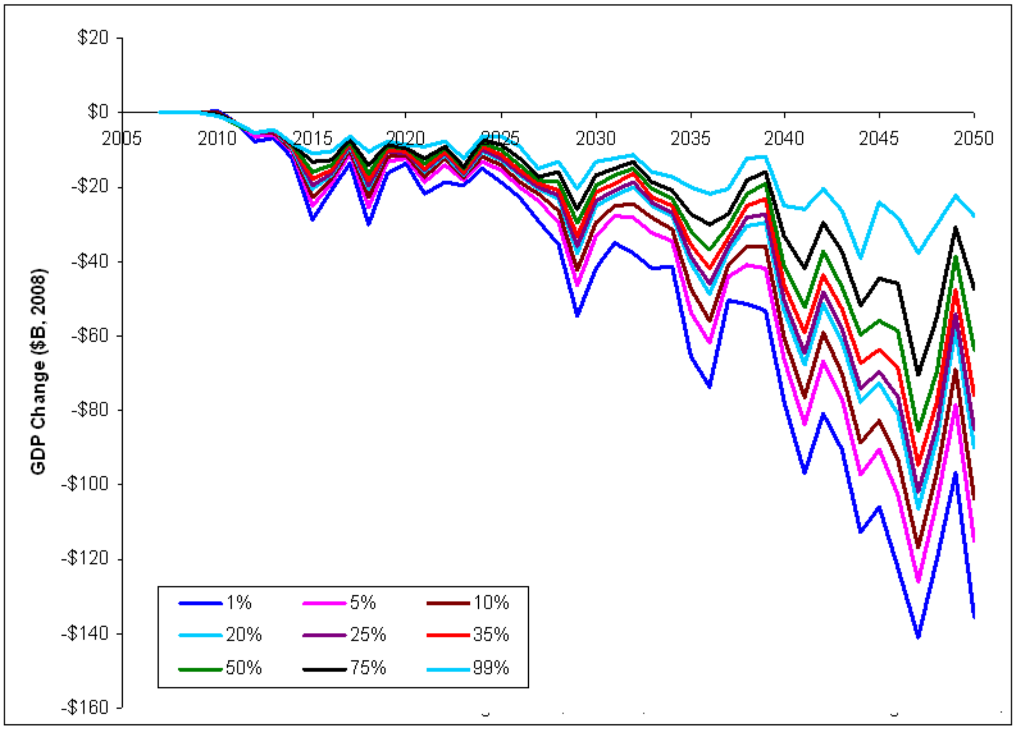

Figure 5. Annual U.S. GDP impacts from climate change.

Examining the estimated impacts for 2015 in Figure 5, the loss at the 99% exceedance probability is on the order of $10 billion, whereas at the 1% exceedance probability the loss is almost $30 billion. However, the same pattern of volatility represented by the climate is used in all the simulations run at the different exceedance probabilities to produce our results. Had a more challenging and increasingly volatile pattern of interannual climatic conditions been used, the economic impacts would be larger and more problematic (due to their more extreme volatility) than the summary monetary impacts of this study indicate.

The variation in employment depicted in Figure 6 shows a similar pattern to the variation in the GDP seen in Figure 5, though there are differences. These differences reflect diversity in the amount of employment demanded per unit of output across industries. Effectively, some industries are more labor intensive than others and experience a greater loss of jobs. For comparable years, say, 2015 and 2028, the losses (dips) portrayed across the two figures are deeper for employment than for the GDP. Certain labor-intensive industries are being affected more than others in these two particular years. In later years, such as in 2045, the patterns of employment and GDP are closer, meaning that more industries are experiencing similar losses in employment. This suggests that impacts of climate change are spreading throughout the entire economy by this time.

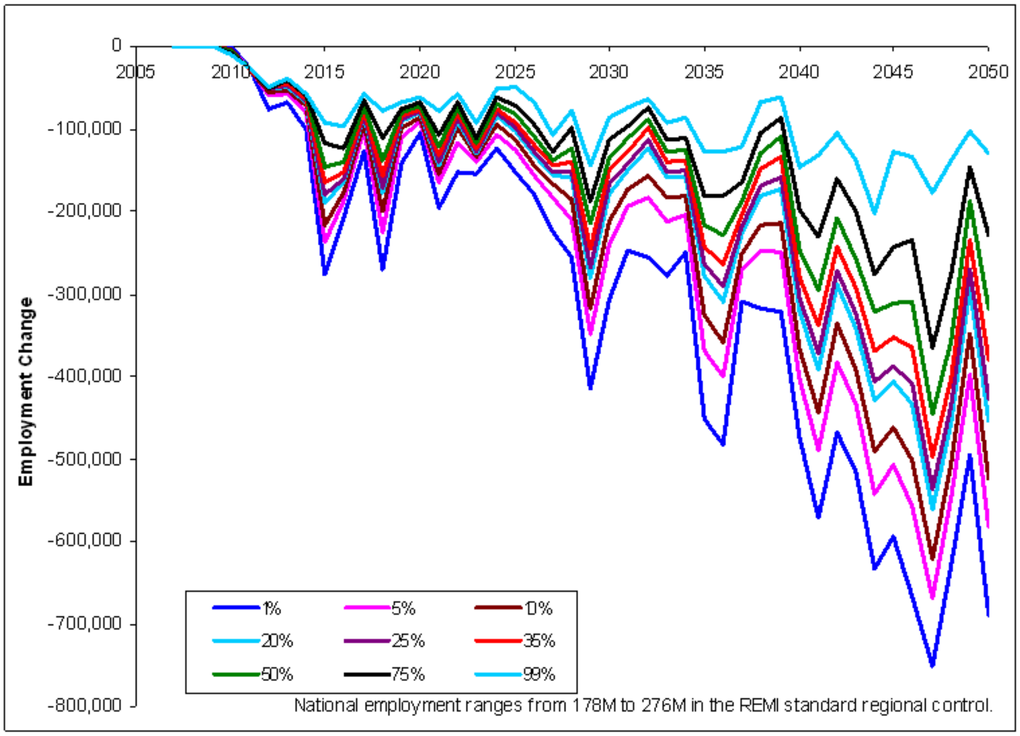

Figure 6. Annual U.S. employment impacts from climate change.

Figure 7 and Figure 8 present the summary-risk losses for the GDP and employment, respectively, as a geographic distribution over individual states. This information conveys the impacts of climate change with which state-level governments and business are likely to contend. The color-coded legend, consisting of ranges of percent impacts, explains how to interpret the figures. Note that it is the percentage of impact, not the amount of impact, that determines the color assigned to each state. Thus, the colors represent the relative nature of the impacts. In Figure 7, only six states, those colored green, experience gains in the GDP as a result of climate change. The GDP losses exhibited by all the other states indicate what it would be worth to avoid climate change even within short-term planning horizons, that is, if mitigation is possible. In Texas, for example, there is a risk of losing about $137 billion over the 40-year period, representing a negative impact to the state's economy of between 0.1% and 0.2%. The employment losses in Figure 8 indicate the pressures policy makers are likely to experience to minimize the impacts of climate change.

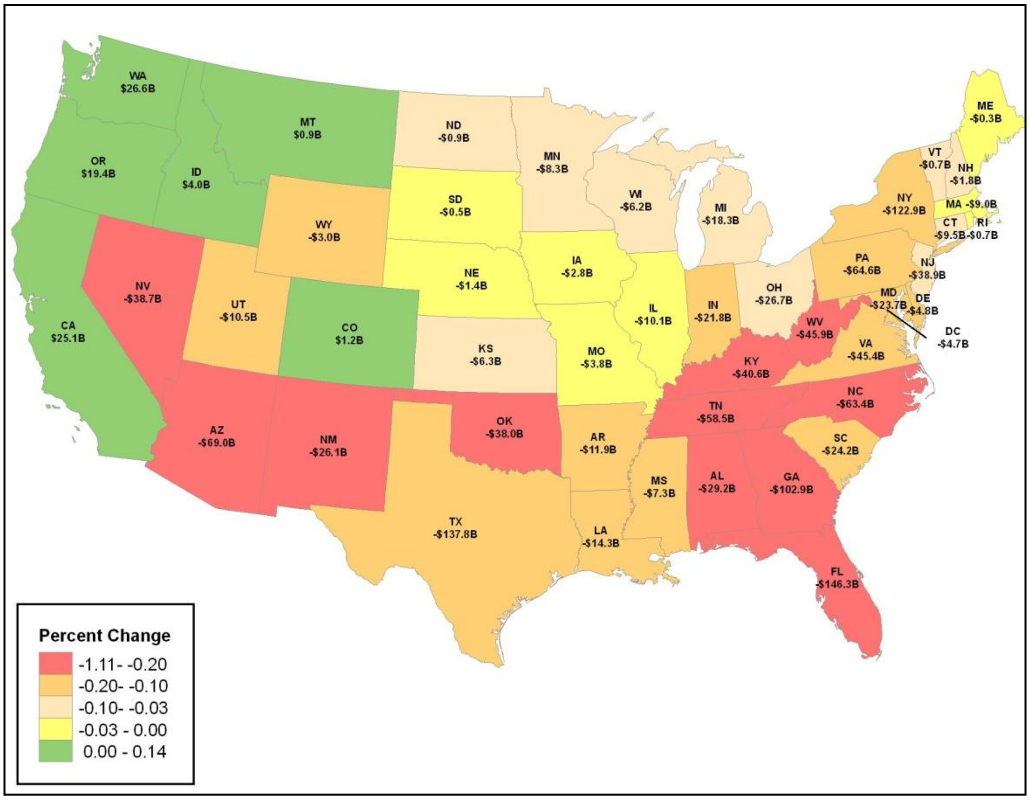

Figure 7. GDP risk (2010–2050) in billions of dollars at a 0% discount rate.

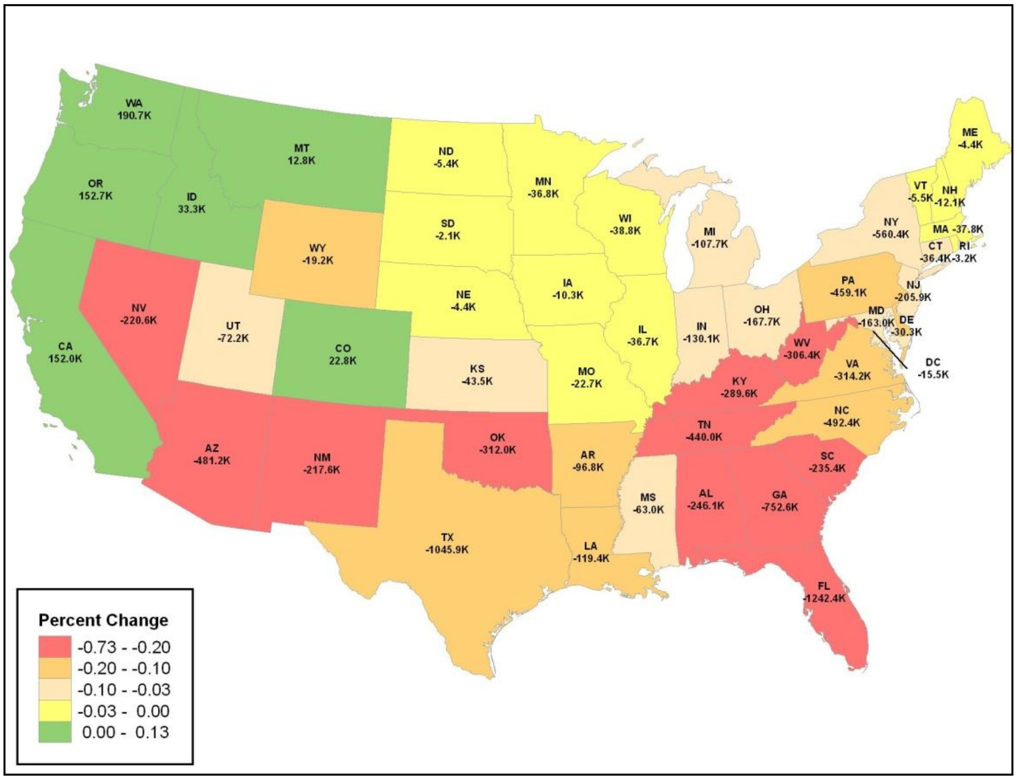

Figure 8. Employment risk (2010–2050) in thousands of labor years.

A more detailed example may help in understanding the analysis results. Despite suffering relatively greater drought conditions on average relative to the rest of the nation, California shows improvements by 2050 because its economic impacts are estimated to become relatively less than those of other states. Populations from other affected states migrate to California and stimulate its economy. This comparative advantage occurs because some states do not have much flexibility in dealing with water shortages, for example, because they have little agricultural irrigation from which water can be diverted. By and large, those states that already suffer water constraints (often due to irrigation loads combined with urban growth in arid regions) have processes in place to adjust to changes in water balances. Through the use of water purchases, irrigation water can act as a buffer against water shortages in other parts of the economy. Because the value added to the economy from certain types of industry is large compared with that for food production, growth in high-value-added industry can compensate for reduced agricultural production. In the near term and at higher exceedance probabilities, California does incur largely negative impacts. Note that the impacts for many states change sign over time, that is, many states alternately experience gains (positive sign) and losses (negative sign).

The Pacific Northwest states show improvement with climate change due to expected increased precipitation and population growth through migration. It is possible, however, that the damage to this region from climate change may be understated. Because this analysis is limited to the annual resolution of precipitation levels (other than capturing the monthly variation for agricultural assessments), we do not capture the impact of seasonal phenomena such as snow. In the Pacific Northwest, the dam system is not designed to accommodate significant changes in the timing of when and how fast snow melts. In the Pacific Northwest, the snow itself acts as a water-storage system and under conditions of warmer temperatures, the increased river flow from melting snow could not be effectively stored behind the dams nor could the additional water be efficiently used in producing electricity. Consequently, the positive impacts shown could be an artifact of our assumptions. On the other hand, migration to the Pacific Northwest may provide positive impacts even if hydropower declines.

Expected urban population growth and an expanding economy in the eastern United States will stress existing water supplies in the future even in the absence of climate change. Consequently, the Northeast and the Southeast experience negative impacts from climate change, even though reductions in long-term precipitation may be minimal. In general, a decreasing exceedance probability (from 50% to 1%) implies that reduced precipitation (i.e., drought) is moving north and east at a continental level, causing more-severe reductions in precipitation in areas that did not noticeably experience reduced precipitation at the larger exceedance probabilities (> 50%). Thus, areas such as Colorado go from having adequate water and benefits in high-exceedance-probability simulations to experiencing losses from reduced water availability in the low-exceedance-probability simulations. Other than in the Pacific Northwest, water availability decreases over time with climate change. Table 3 gives the numerical values of GDP impacts from 2010 to 2050 with all three discount rates. Also included in the table are the impacts on employment (2010–2050) and from population migration (shown only for the year 2050).

Employment changes and population migration represent changes in material conditions, as opposed to a change in monetary status for GDP impacts, and thus are not discounted.

Table 3. National and State-Level Risk (2010–2050)

Summary of Climate Impacts (2010-2050)

Region	Change in GDP (Billions of 2008$) Discount Rates 0.0%	1.5%	3.0%	Change in Empl. (Thous. Labor-Years)	Change in Pop. (Thous. People)
United States	**-$1,204.8**	**-$790.3**	**-$534.5**	**-6,862.7**	**0.0**
Alabama	-$29.2	-$18.9	-$12.6	-246.1	-10.8
Arizona	-$69.0	-$45.8	-$31.2	-481.2	-14.8
Arkansas	-$11.9	-$7.6	-$5.0	-96.8	-2.4
California	$25.1	$16.6	$11.5	152.0	115.7
Colorado	$1.2	$0.4	$0.0	22.8	15.3
Connecticut	-$9.5	-$6.3	-$4.3	-36.4	4.7
Delaware	-$4.8	-$3.1	-$2.1	-30.3	0.0
D.C.	-$4.7	-$3.1	-$2.1	-15.5	0.5
Florida	-$146.3	-$97.5	-$66.9	-1,242.4	-55.5
Georgia	-$102.9	-$67.7	-$45.9	-752.6	-40.0
Idaho	$4.0	$2.5	$1.6	33.3	6.9
Illinois	-$10.1	-$5.1	-$2.5	-36.7	15.7
Indiana	-$21.8	-$12.9	-$7.8	-130.1	-4.0
Iowa	-$2.8	-$1.4	-$0.6	-10.3	3.1
Kansas	-$6.3	-$4.1	-$2.7	-43.5	2.3
Kentucky	-$40.6	-$24.9	-$15.6	-289.6	-21.6
Louisiana	-$14.3	-$9.4	-$6.3	-119.4	-0.9
Maine	-$0.3	-$0.2	-$0.2	-4.4	2.5
Maryland	-$23.7	-$15.6	-$10.5	-163.0	0.1
Massachusetts	-$9.0	-$5.9	-$4.1	-37.8	12.9
Michigan	-$18.3	-$11.2	-$7.1	-107.7	7.1
Minnesota	-$8.3	-$4.9	-$2.9	-36.8	7.6
Mississippi	-$7.3	-$4.7	-$3.1	-63.0	-0.8
Missouri	-$3.8	-$2.2	-$1.3	-22.7	8.3
Montana	$0.9	$0.6	$0.4	12.8	2.9
Nebraska	-$1.4	-$0.8	-$0.4	-4.4	2.5
Nevada	-$38.7	-$26.2	-$18.1	-220.6	-2.8
New Hampshire	-$1.8	-$1.2	-$0.8	-12.1	2.6
New Jersey	-$38.9	-$25.8	-$17.6	-205.9	3.6
New Mexico	-$26.1	-$17.9	-$12.7	-217.6	-8.3
New York	-$122.9	-$80.5	-$54.4	-560.4	7.2
North Carolina	-$63.4	-$41.6	-$28.1	-492.4	-19.8
North Dakota	-$0.9	-$0.5	-$0.3	-5.4	0.8
Ohio	-$26.7	-$16.1	-$10.0	-167.7	1.7
Oklahoma	-$38.0	-$25.2	-$17.2	-312.0	-15.3
Oregon	$19.4	$12.5	$8.3	152.7	20.5
Pennsylvania	-$64.6	-$42.4	-$28.7	-459.1	-7.7
Rhode Island	-$0.7	-$0.5	-$0.3	-3.2	1.8
South Carolina	-$24.2	-$15.9	-$10.7	-235.4	-10.2
South Dakota	-$0.5	-$0.3	-$0.2	-2.1	1.3
Tennessee	-$58.5	-$37.3	-$24.4	-440.0	-23.0
Texas	-$137.8	-$91.0	-$61.9	-1,045.9	-28.5
Utah	-$10.5	-$6.9	-$4.6	-72.2	2.2
Vermont	-$0.7	-$0.4	-$0.3	-5.5	1.0
Virginia	-$45.4	-$29.7	-$20.1	-314.2	-5.9
Washington	$26.6	$17.0	$11.2	190.7	29.5
West Virginia	-$45.9	-$27.7	-$17.0	-306.4	-34.5
Wisconsin	-$6.2	-$3.7	-$2.2	-38.8	6.6
Wyoming	-$3.0	-$1.9	-$1.3	-19.2	-0.5

Migration across states is often based on comparative advantage. Even if a given state economy is having difficulties, it may be having less difficulty than other states. If we look at the state of New York, we see that the summary impact of climate change from 2010 to 2050 is a loss of $122 billion with a 0% discount rate. This loss is reduced to $81 billion with a 1.5% discount rate and to $54 billion with a 3% discount rate. The drop is dramatic because much of the impact occurs in the later years. Note that the reduced economic activity does reduce employment by 560,000 labor years by 2050 even though the population has risen by 7,200 people due to in-migration from the even-more-affected surrounding states. This means that the unemployment in New York is increasing even more than the drop in economic activity would indicate. If the other states were less affected by climate change, New York would have experienced large out-migration.

Table 4 presents our estimated risks to selected industries from climate-change uncertainty. The results shown are presented in terms of contribution to the GDP. The impact on sales and revenue would be larger, varying between less than 1.5 times larger for retail sales to more than 3.0 times larger for manufacturing. Due to construction, especially of power plants to augment lost hydroelectric capacity, positive effects in terms of economic value are experienced by utilities, electric equipment, and other manufacturing. Construction experiences a decline because of the overall national decline in economic growth. Transportation (not shown) sees a net zero economic impact, despite an overall reduction in economic activity, because of the added need for interstate trade, especially for food. Many professional services, including medical, suffer a decline because unemployment constrains additional spending. Agriculture-dependent industries, such as the chemical industry, encounter disproportional declines. Like agriculture, climate change strongly affects the mining industry because of the mining industry's relatively rigid dependence on water.

Table 4. Selected Industry Risks (2010–2050)

Selected National-Level Industry Impacts 2010–2050 (0% Discount Rate, Billions 2008$)				
Oil and gas extraction	-$9.4		Food manufacturing	-$82.3
Mining (except oil and gas)	-$86.3		Beverage and tobacco product manufacturing	-$29.4
Support activities for mining	-$7.3		Chemical manufacturing	-$18.2
Utilities	$13.6		Wholesale trade	-$45.3
Construction	-$30.8		Retail trade	-$127.2
Wood product manufacturing	-$1.1		Broadcasting, Telecommunications	-$28.1
Nonmetallic mineral product manufacturing	-$3.3		Monetary authorities, funds, trusts, financials	-$34.1
Primary metal manufacturing	-$2.4		Securities, commodity contracts, investments	-$39.9
Fabricated metal product manufacturing	-$3.7		Real estate	-$38.2
Machinery manufacturing	-$4.2		Professional and technical services	-$41.4
Computer and electronic product mfg.	-$10.3		Administrative and support services	-$21.2
Electrical equipment and appliance mfg.	$1.4		Ambulatory health care services	-$66.8
Motor vehicles, bodies & trailers, parts mfg.	-$8.8		Food services and drinking places	-$19.9

Conclusions

This study focuses on the uncertainty and volatility of climate change rather than on the development of a predictable and smooth transition to expected future conditions. The uncertainty associated with climate change, combined with the consequences it entails, defines the risk from climate change. Further, the volatility of conditions over time means the risk assessment needed to go beyond a static analysis and address the dynamics of the impacts and the response. The uncertainty within the results of the ensemble of IPCC data sets represents an accepted notion of climate uncertainty. These results do not, however, represent a formal quantification of uncertainty because they do not, for example, address threshold conditions where self-reinforcing phenomena lead to as-yet unrecognized threats, nor do they contain detail on phenomena, such as cloud formation, that could change our understanding of climate dynamics. The formal characterization of climate uncertainty for refining the risk assessment is one of the next steps in improving the analysis presented here.

The detailed, time-dependent approach used in the analysis shows the additional early consequences of the volatility in climate change. The impacts across 70 industries and 48 states demonstrate the interrelationships that produce consequences different from those consequences that would be indicated by the analysis of individual states or economic sectors in isolation. To date, this is the first study to address the interactive effects of climate change across the U.S. states and to deal explicitly with the problems of interstate population migration as a consequence of climate change.

Our risk assessment only considers the loss in the absence of mitigation or any other climate policy. The value of the loss, on the order of a trillion (2008) dollars for the United States at a 0% discount rate, can be interpreted as an upper limit on how much society could be willing to pay for a successful mitigation of climate change, even over the near term. We feel the risk-informed approach used in this work relates physical climate science to the societal consequences and thus directly helps inform policy debate. The integrated process of (1) recognizing uncertainty in climate-change forecasts, (2) transforming climate-change phenomena into physical impacts that affect economic and societal processes, and (3) converting those physical impacts to time-dependent changes in economic and societal conditions provides the end-to-end assessment capability recommended by the Obama Administration (Holdren 2009). By knowing what aspects of climate change have the most severe human consequences, this type of analysis can also guide and prioritize the scientific research to better quantify the most critical phenomena. We want to reemphasize that the methods of this study reveal how compelling risk derives from uncertainty, not certainty. The greater the uncertainty, the greater the risk. *It is the uncertainty associated with climate change that validates the need to act protectively and proactively.*

A fundamental shortcoming of this study is its focus on the United States. Although understanding the U.S. risks from climate change is a necessary foundation for informed policy debate (GAO 2009), climate change is global, and global turmoil affects the United States (CNA 2007). Our analysis assumes that the rest of the world fully accommodates climate change and that it can absorb a volatile U.S. export-and-import situation. The next phase of this work on the impact of climate change will include the characterized risks to the rest of the world and the implications of these risks on those for the United States. Those efforts must also recognize the pressures climate change can exert on geopolitical stability and on international socioeconomic relationships.

Appropriate to our purpose, we used the IPCC AR4 ensemble as the proxy for the uncertainty in climate change. As climate science advances and improved estimates of uncertainty become available, future risk assessments should include the then best understanding of the uncertainty. The methods for quantifying uncertainty in combined physical and societal simulations over time and across geographic regions require further development. Moreover, confidence in the results from physical and socioeconomic models can only occur through formal validation and verification (V&V) efforts. We are extending our long-standing research on infrastructure surety, systems reliability, probabilistic risk assessment, and V&V to improve statistically meaningful estimates of climate-change uncertainty.

In the conventional discourse on the impacts of climate change, mitigation denotes the (1) reduction in anthropogenic and natural greenhouse gas (GHG) emissions, (2) capture and storage of GHG from industrial processes such as geological sequestering or directly from the atmosphere such as by reforestation, or (3) alleviation of the effects of increased GHG concentrations through engineered efforts such as geoengineering.

Conventional adaptation denotes efforts to maintain the status quo socioeconomic conditions, to the extent possible, in the face of expected changes in environmental conditions such as through drought-resistant crops and seawalls. Because we devote our analysis to the impacts of climate change in the absence of policy initiatives, we did not consider the reliability or risk assessment of mitigation and adaptation policies. The methods developed in our study, however, are equally applicable to the risk assessment of policies. The larger challenge lies not in the technical difficulties of such an analysis but rather in the communication of the risk and uncertainty in a manner that connects to the vital concerns of the policy makers.

We have only systematically addressed the one dimension of precipitation uncertainty. For instance, we ignored disease vectors and extreme weather conditions like storms. We did not consider uncertainty in migration and trade dynamics. More generally, we did not confront the combined uncertainty across the many other dimensions of climate-change uncertainty that have consequences for society. Modern society depends on a complex network of infrastructure with its interdependencies, vulnerabilities, and potential for cascading failure modes. Through the National Infrastructure Simulation and Analysis Center (NISAC) program with the Department of Homeland Security, housed at Sandia National Laboratories and Los Alamos National Laboratory, many of the capabilities needed to extend this study for considering those added dimensions of risk already exist.

To sum up, despite the room for improvement, we feel the current study does establish a process for improved and more-meaningful risk assessments of climate change than is currently present in the literature. More importantly, the study offers a systematic foundation for policy debate. Uncertainty induces debate. In the presence of absolute certainty, there are no facts left to debate. This analysis used the current understanding of climate-change uncertainty to unambiguously quantify risk. The future evolution of policy on climate change will rest on refinements of the methods reported here and on continuing improvements in the quantification of uncertainty for both climate change and its consequences.

All sources cited in the Executive Summary are listed in the References section of the body of the report. The complete citation for this report is as follows: Backus, G., T. Lowry, D. Warren, M. Ehlen, G. Klise, V. Loose, L. Malczynski, R. Reinert, K. Stamber, V. Tidwell, V. Vargas, and A. Zagonel. (2010). *Assessing the Near-Term Risk of Climate Uncertainty: Interdependencies among U.S. States*. SAND 2010-2052. Albuquerque, NM: Sandia National Laboratories. https://cfwebprod.sandia.gov/cfdocs/CCIM/docs/Climate_Risk_Assessment.pdf.

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Acronyms and Abbreviations

AMO	Atlantic Multidecadal Oscillation
AOGCM	atmospheric and ocean global-circulation model
AR4	IPCC Fourth Assessment Report
BEA	Bureau of Economic Analysis
CCDF	complementary cumulative distribution function
CDF	cumulative distribution function
CGE	computable general equilibrium
CO_2	carbon dioxide
CONUS	continental United States
ENSO	El Niño Southern Oscillation
GDP	gross domestic product
GSP	gross state product
GHG	greenhouse gas
IPCC	Intergovernmental Panel on Climate Change
kWh	kilowatt hour
MWh	megawatt hour
NAICS	North American Industry Classification System
PCMDI	Program for Climate Model Diagnosis and Intercomparison
PDSI	Palmer Drought Severity Index
PRTP	pure rate of time preference
REMI	Regional Economic Models Incorporated
Sandia	Sandia National Laboratories
SMSA	Standard Metropolitan Statistical Area
SPI	standard precipitation index
SRES	Special Report on Emissions Scenarios
USAID	United States Agency for International Development
USD	U. S. dollars
USGS	U.S. Geological Survey

No reasonable person will wait for certainty before he decides on action or inaction.

Noam Chomsky, American philosopher
(Chomsky et al. 1968)

All models are wrong but some are useful.

George Box, Statistician (Box and Draper 1987)

I don't think the American public understands [there's] a reasonably high probability some very bad things will happen. They fundamentally don't understand that, because if they really felt that, then they would do something about it.

Steven Chu, U.S. Secretary of Energy (Chu 2008)

1 Overview

Climate science in support of efforts by the Intergovernmental Panel on Climate Change (IPCC) further establishes and defends the reality of climate change (Hegerl et al. 2007). Uncertainty analyses of climate change, such as those noted in Randall et al. (2007), seek to improve the estimates of future conditions and reinforce confidence in the predicted climate impacts. The IPCC Fourth Assessment Report (AR4) portrays the sense of confidence and likelihood by describing uncertainty in terms of probability (CCSP 2009; IPCC 2005; Manning 2006). For example, the discussion may note that "for some regions, there are grounds for stating that the projected precipitation changes are likely or very likely. For other regions, confidence in the projected change remains weak" (Christensen et al. 2007). Other published uncertainty analyses focus on the impacts of the policies necessary to mitigate climate change (Barker et al. 2006) and the extent to which mitigation reduces the impacts of climate change (Washington et al. 2009).

In the study described herein, we address the uncertainty in the impacts of climate change within the context of risk assessment. From a policy perspective, the incentive to act comes by comparing the risk (cost) of inaction with the cost of action to mitigate climate change. Risk is often characterized in terms of probability and consequence. There is a spectrum of conditions (or events) involved with climate change for assessing risk. At one end of the spectrum are those conditions that may occur frequently (high probability) and result in minimal damage (low consequence). At the other end of the spectrum are conditions that do not occur frequently (low probability) but may be life changing or catastrophic (high consequence) if they do occur.

The clearest analogy for the risk approach is the value of an insurance policy or a safety precaution. Most likely you will not be involved in a traffic accident the next time you drive to work, but you should wear a seat belt nonetheless to manage the risk of those low-probability and potentially high-consequence events. Likewise, you are fairly confident your house will not burn down tonight, but you still carry homeowner's insurance. On the other hand, you would feel very uncomfortable sending your family on a plane that had a 10% chance or even a 1% chance of catastrophic failure. We use an insurance approach in this study to estimate the risk from climate change. The insurance approach for risk assessment has also been used in other studies to characterize the cost of climate change (Schock et al. 1999).

For climate science, the discussion tends to revolve around justifying action through the high levels of certainty of when and where a climate impact will occur. Science strives to maximize the probability that its claims are true. For example, the IPCC "Summary for Policymakers" focuses on the likelihood of physical impacts from climate change compared to historical conditions. There are five measures of "likely," going from greater than 99% to greater than 50% probability, whereas there are only three measures of "unlikely," with the lowest measure for conditions having less than a 5% probability. (IPCC 2007d). In the realm of risk-assessment, conservative science's best estimates are considered "optimistic" rather than "conservative." Risk assessment is more concerned with the low-probability, higher-consequence conditions than with the high-probability, lower-consequence ones. Risk assessment in this study concentrates on the implications for decision making from climate-change uncertainty rather than from the expected values. A focus on an expected value may lead one to believe, for example, that the trend in precipitation over time is more constant than what the uncertainty indicates. An expected value could give the impression that precipitation should drop by a similar amount year after year. From an uncertainty perspective, however, there will be years where there is more precipitation followed by years where there is less precipitation.

This study emphasizes the low-probability, high-consequence conditions that may dominate the spectrum of risk. As an example, over the long-term, climate change represents one of the few existential threats to humanity (Ban 2009). The most recognized other risk is a catastrophic asteroid collision with Earth. Yet the risk of catastrophic climate change is currently estimated to be many times more probable than a catastrophic asteroid collision (Boslough 2010). Should the extent of climate change cross a threshold where geophysical processes reinforce man-made climate change, the long-term consequences could be catastrophic (Keller et al. 2008). Nonetheless, because we only address the risk of climate change through the year 2050, we do not need to consider the possibility of catastrophic climate change in this study.

Studies have shown that humans are extremely limited in their ability to estimate the future conditions of systems with feedback and delays (Sterman and Sweeney 2007; Sterman 2008). Coupled atmospheric and ocean global-circulation models (AOGCMs) and macroeconomic forecasting models containing feedback and delays are the only means available to assess the dynamics and impacts of future climate change (Murphy et al. 2004). Because decisions for climate policy need to be made before climate scientists have resolved all the relevant uncertainties, the goal of risk assessment is to inform decision makers of the risk in light of the current understanding of uncertainty. The cost associated with the risk represents the cost of inaction. Comparing the cost to avoid the risk (action) to the cost of accepting the risk (inaction) can then inform policy decisions. Presuming there is still time to mitigate climate change, the anticipated future time window needed to effectively combat climate change and the delays in implementing effective policies mean that policy makers have no choice but to use the best currently available information with all its limitations. The alternative to using the AOGCMs and macroeconomic models is to use even less justifiable information.

A “perfectly valid” analysis of future climate-change impacts is also outside the reach of science or numerical methods. There are entirely too many details to ever completely know. In any analysis, there must be simplifying assumptions to make the analysis feasible. The best assumptions are those that do not affect the conclusions—even though they do affect the details of the analysis results. Pragmatically, knowledge is routinely too limited to verify whether assumptions are benign. Despite its shortcomings, formal analysis furnishes one of the few comprehensible foundations that can support a rational basis for decisions. To make this study as transparent as possible, we have explicitly stated as many of the assumptions as possible, thereby allowing critical review and public scrutiny. We recognize that the analysis here is necessarily imperfect, but we believe its imperfections do not negate the message of the study. In addition, to make this study accessible to a broad audience, we have occasionally avoided presenting all the technical caveats that would be appropriate for a specialist in any one of the disciplines used to develop the study.

Vast amounts of information and numerous studies describe in detail the countless aspects of climate change. Just like everyone else, policy makers have competing demands on their finite time to address innumerable priorities, from unemployment to nuclear proliferation. Ensuring that policy makers understand all the subtle features of climate change can only ensure that there is information overload and lack of action in terms of implementing policy. Unavoidably, the use of science to inform policy making is a trade-off between the best information science can offer and the limiting, but more-critical, realities of the societal decision-making process.

The discriminating use of salient science can inform policy, whereas detailed absorption of expert-level research cannot (NRC 2009). Policy makers do not have the time to argue which bit of today’s climate science is the best in attempting to reach a consensus on policy. A consensus about the reality of climate change among climate scientists does not lead to a “consensus” on policy, i.e., what to do about climate change, in an immediate or a direct manner. Science focuses on facts, whereas decisions about policy are always influenced by an array of human predilections. Given that it may be difficult to obtain a consensus on policy, it is still possible to construct a representation of the future as the basis for comparing alternative solutions to the problem at hand. For this agreement, an anchor is needed upon which policy makers can tackle the issues that challenge the interests of disparate stakeholders. We refer to such an anchor as a *referent*. While a referent is often based on extensive analysis, its use as a starting point for addressing policy alternatives is more important than its absolute accuracy. Importantly, several referents (or data sets) are used in this study to determine whether actions taken will make the future better or worse. There are referents for each component of the analysis, that is, future climate, hydrological, and macroeconomic conditions. A referent only acts as a point of comparison between the conditions that are specified in the referent and (uncertain) alternative conditions.

Using computer models to make any prediction about state-level economies in 2050 will almost certainly be highly inaccurate, but this approach is the only coherent option available to inform current decision making. In the context of a referent, an imprecise prediction can be useful for comparing options if we assume that such a prediction (1) adequately depicts the future relative to the choices to be made, and more importantly, (2) represents a mutually agreed basis from which stakeholders can debate alternatives on common ground. While better science could reduce some of the uncertainty, this reduction will occur after the time frame for effective policy action. The IPCC climate projections (IPCC 2007c), along with any limitations and nuanced caveats associated with their usage, represent the best, if not the only, timely choice available. The IPCC analyses represent the most visible climate reference for framing the national and international assessment of climate change.

Our motivation for conducting this study is to add a perspective to the climate debate that the larger the uncertainty in climate-change impacts, the larger the implied risk. The policy impetus to contain the risk of climate change is no different from that for an asteroid collision or for acts of terrorism. As such, climate uncertainty does not sanction policy inaction. In this study, we use a risk-assessment process that recognizes the uncertainty of climate science and the impacts of future climate change while further balancing exacting science with the imperfect yet effective application of that science. The formal use of uncertainty quantification, which is a key component of impact evaluation, is a well-established process (Matott et al. 2009; Helton 2009; Räisänen and Palmer 2001; Dessai and van der Sluijs 2007) and has been used in this study. Uncertainty quantification is the process that makes it possible to forge a functional statement about future outcomes despite uncertainty.

A discussion of climate sensitivity can help illustrate how uncertainty relates to risk assessment. The term *climate sensitivity* combines the concepts of how sensitive the climate is to a doubling of greenhouse gas (GHG) concentrations and the uncertain range of temperature associated with a given concentration of these gases. While the best estimates of global warming (rise in the global mean [average] temperature) by the year 2100 are on the order of 2º to 4ºC, the uncertainty is relatively large, with the probability density function on climate sensitivity dominated by a ”long tail” where the probability of much more severe temperature impacts has significance. As shown via the color-coded legend in Figure 1-1, various studies have attempted to define this uncertainty (Hegerl et al. 2007). Other studies indicate that this uncertainty may be unavoidable no matter how much climate science evolves or how sophisticated the computer simulation of climate becomes (Roe and Baker 2007).

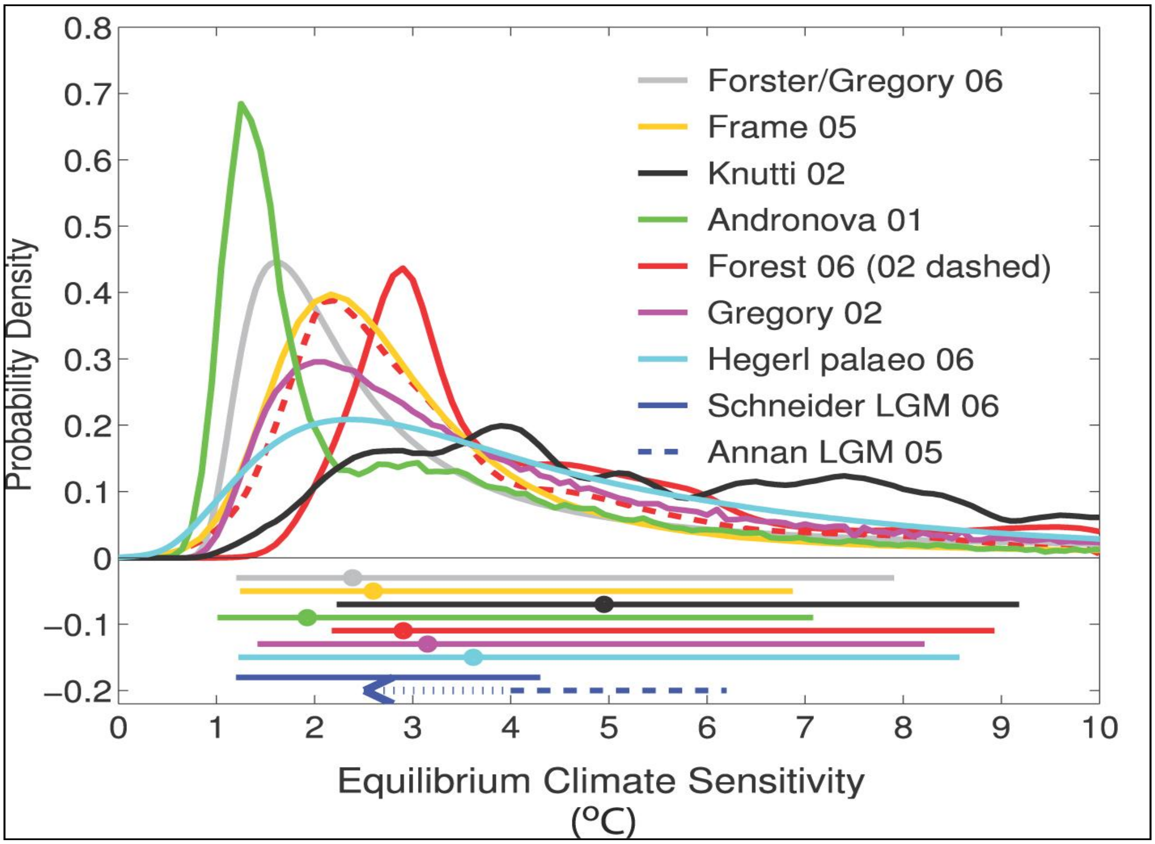

Figure 1-1. The "long tail" of climate sensitivity. Source: Hegerl et al. (2007).

For those unfamiliar with the notion of the long tail, we look further at Figure 1-1. Each curve is associated with a color and identified by author and date in the legend. Each curve contains a tail skewed to the right-hand side that is the portion of the distribution where the values decline more gradually than near the peak or on the left of the peak. Thus, many tails, in fact, are visible in the figure. The notion of the "long tail" signifies that all these studies are making a statement that a long tail of uncertainty is present with regard to the global rise in temperature. We take one curve to point out common and unique aspects of the distributions. The yellow curve, estimated in the study by Frame et al. (2005), shows that the most likely rise in temperature will be roughly 2°C, as reflected by the peak of the distribution. However, the mean or average estimate of the distribution, as indicated by the dot on the horizontal yellow bar below the x-axis, is roughly 2.75°C. The bars represent the 5% to 95% confidence intervals of the associated curves. The reason that the average estimate is larger than the most likely estimate is due to the influence of the tail of that distribution that includes higher temperatures, which are possible but less likely.

The combination of the probability and the consequence of climate change all along any probability distribution of climate sensitivity determines the estimated risk of climate change from that distribution. The risk is then the value of insuring against all the consequences associated with the distribution of, in the above example, temperatures. (Weitzman 2007). Because the climate uncertainty is a stumbling block in addressing climate change, our goal is to estimate the risk using the existing understanding of climate uncertainty and thereby provide decision makers with the pivotal piece of information needed to weigh options for intervention (Dessai and van der Sluijs 2007).

The consequence of a negative event is often expressed in economic terms, such as the monetary value of a loss or the number of jobs lost. And because human behavior is so complex, there is even greater uncertainty in the prediction of future economic conditions than there is in the prediction of climate change alone. Yet, despite uncertainty about the future, cost-benefit analyses are conducted on a daily basis as aids for policy makers on issues of critical importance to the nation such as health care, social security, and defense. Similarly, individuals weigh the costs and benefits of taking certain actions, like purchasing insurance, to minimize risk for themselves and their families.

In the economic and scientific literature, the physical impacts and their resulting cost impacts from climate change are often encapsulated by the single dimension of temperature (Nordhaus 1993; Hope and Alberth 2007). Costs are often estimated as linear or quadratic functions of temperature (Ackerman and Finlayson 2006; Tol 2002a). The impacts for temperature are generally indirect and through long chains of inferred relationships.

In this study, we use precipitation to determine the hydrological impacts directly affecting economic activity. The precipitation levels with related uncertainly that we use in our analysis are based on the existing ensemble of the IPCC Program for Climate Model Diagnosis and Intercomparison (PCMDI) runs (Meehl et al. 2007a). We additionally incorporate the consequences of precipitation volatility and associated temperature conditions. We take this approach of viewing economic impacts through the lens of water availability and its hydrological implications because it allows us to conduct a direct tangible analysis of impacts on the U.S. economy (Ackerman and Stanton 2008). As explained in detail in subsequent sections, this risk assessment study is composed of three components: (1) determining climatic conditions at the state level across the range of uncertainty, (2) imposing these conditions on a hydrological model to map critical climate impacts to U.S. state-level physical conditions that may affect the economy, and (3) using a mature, dynamic state-level macroeconomic model to capture interacting demographic and economic responses.

We estimate the macroeconomic impacts resulting from the probabilistic lessening in precipitation from climate change. That is, the analysis considers how the amounts of precipitation are not a single estimate but a rather a distribution of possibilities. Across simulations of varying amounts of precipitation, we calculate the hydrological conditions and adjustment efforts to limit future economic cost and maintain economic viability. Kundzewicz et al. (2007) provides an extensive IPCC overview of the climate-modeling, hydrological, and economic considerations related to climate-induced changes in water resources. In our analysis, we explicitly estimate the interacting impacts across the 48 states in the continental United States (CONUS) including the District of Columbia with detail across 70 economic sectors. We have included dynamic (time-dependent) changes in costs, consumption, employment, and population migration.

We do not attempt to apply a cost to human suffering or to ecological damage beyond the effects that such consequences of climate change may have on economic activity by 2050. Thus, for example, there is no cost calculated for loss of human life and for plant and animal species becoming extinct. However, the study does calculate how the macroeconomic impacts of climate change have cascading affects on economic activity across many sectors, such as health care and social assistance.

Our study evaluates how consumers and industry respond (adjust) to the shifting economic and physical conditions created by climate change. These adjustments moderate the economic impacts that would otherwise occur, and thus any integrated economic assessment needs to incorporate the actions that people take to compensate for negative events. When there is a perceived threat to the economy, people in their different societal roles make changes in their behaviors to accommodate the new circumstances. This analysis assumes that individuals and industry maintain the behavioral response characteristics as they have historically (see Sections 3.2 and 3.3). We feel that using real-world behaviors is a more realistic approach than simulating the choices people make based on the commonly used economic assumptions of clairvoyant optimality (Manne et al. 1995; Nordhaus and Yang 1996; Ackerman and Nadal 2004). Such optimal assumptions are grounded in the belief that we can know the future, and because we know that future, we can make perfect decisions. The projected climate reality is not consistent with such assumptions. Modern behavioral economics also supports this more pragmatic view of human decision making (Kahneman 2002).

The relatively myopic economic behaviors simulated in this study are consistent with historical behaviors (REMI 2007). Although the activities may be less than optimal from a longer-term perspective, the activities do capture the impacts that have the greatest relevance to current policy makers. In the absence of quantifying the near-term cost, the need to address climate change seems more remote and has a diluted sense of urgency.

Because this study focuses only on future impacts through the year 2050, the myopic nature of assumed human behaviors used in the analysis does create a horizon problem. Responses to climate change that are made between now and 2050, such as continuing to use ground water and developing coastal areas to gain access to (rising levels of) the sea could make the consequences of future climate change much worse—not because the climate is worse than expected but because prior actions have reduced the physical and societal resiliency to deal with the climate (Pielke et al. 2008). Beyond the year 2050, more-severe outcomes and cost to future generations remain obscured and absent from the cost calculations. Expected impacts beyond 2050 are likely to grow in severity and have large financial consequences. Hope and Alberth (2007) indicate the cost in the low probability (5%) part of the uncertainty tail discussed previously to be a 4% loss of U.S. gross domestic product (GDP) in the year 2100 and a nearly 15% loss of GDP in the year 2200. Although the U.S. political process may eventually be able to tangibly address uncertainty in policy concerns to the year 2100, the justification for implementing policy in the present needs to hinge on the tangible near-future cost of inaction.

All analyses in this study correspond to the IPCC Special Report on Emissions Scenarios (SRES) A1B scenario. The IPCC considers the A1B to be a “balanced” scenario of economic growth with expanding renewable energy use. We have not addressed variation in carbon dioxide (CO_2) emissions or mitigation efforts to reduce emissions. Thus, for example, actions taken by individuals to cut back on how much they drive their vehicles because of concern about the planet's health are not captured in this study. We determine the impacts in the absence of mitigation policy and without the consideration of varying CO_2 emissions.

Figure 1-2 presents an overview of the three major steps in our analysis process. We start with the IPCC A1B ensemble, as depicted in the left-hand box, Specifically, we use the PCMDI data set containing the precipitation data (Leroy et al. 2008). We use results from these runs to assemble the statistical distribution of potential climatic futures for precipitation and temperature conditions with uncertainty between 2010 and 2050. Next, using the Sandia hydrological model, we map the temperature and precipitation data to the CONUS county and state levels to determine the availability of water for selected industries within each state, as represented in the middle box. The water demand in each state is derived from the macroeconomic base-case forecast. During the third step, noted in the right-hand box, we employ the Regional Economic Models Incorporated (REMI) macroeconomic model (REMI 2009) to determine the cost of adjusting water usage to match availability and calculate the resulting macroeconomic impacts due to revisions in the comparative economic advantage of each state.

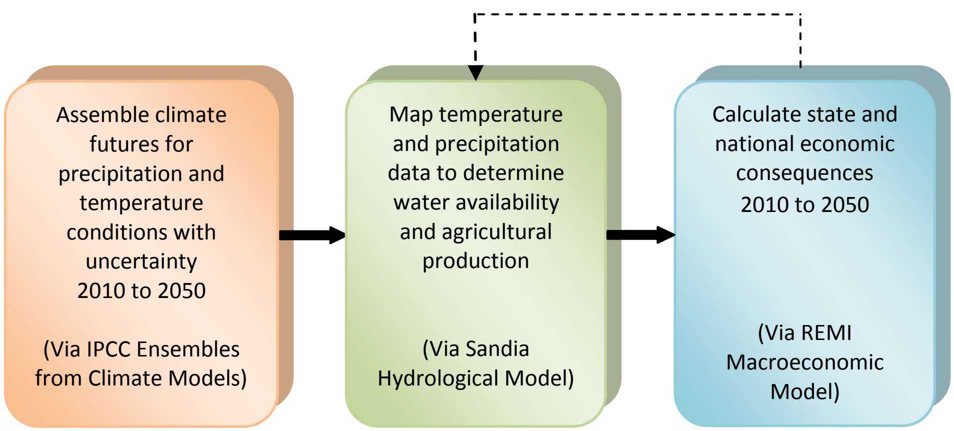

Figure 1-2. Overview of the analysis process.

If the impacts on the economy are so large that they in turn produce sizable impacts on the estimated water availability, the REMI model and the hydrological model can iterate until these models adequately converge. The backward dashed arrow in Figure 1-2 reflects the potential case of iteration. In this study, multiple iterations would only change the result of a single pass through the models on the order of a hundredth of a percent at the national GDP level. Therefore, reported values are taken from the results of a single pass of these models for a set of probabilities across the range of uncertainty.

Our analysis is U.S.-centric in that it only considers climate impacts within the United States. We do not consider the impacts of climate change on the rest of the world, nor how the rest of the world deals with U.S. demands for goods and services in this uncertain future. Had the rest of the world been considered in the analysis and been similarly affected as the United States, there would be secondary (added) impacts beyond those calculated for the United States in this study. The analysis has geographic resolution down to the state level to inform U.S. policy makers from government and corporate arenas about the risk of climate change in terms that are meaningful to them (GAO 2009). In addition, the study only covers the period from 2010 to 2050 to maintain a connection to the pragmatic time horizon on which the numerous priorities of corporate, state, and national policy will play out.

1.1 Concepts and Terms

Our study of climate change embraces work from numerous disciplines, including climate science, economics, statistics, hydrology, geology, risk assessment, uncertainty quantification, modeling and simulation, and public policy. Each of these disciplines has its own way of conveying information and uses terms that practitioners in the particular discipline understand but which may convey different meanings to people in other disciplines or walks of life. For this reason, we have identified several concepts and terms that are used in this study to have the meanings listed below. In addition, because we want this work to be accessible to a general audience, we have avoided distinguishing many technical caveats.

Concept or Term	Meaning
confidence interval	A term used in the description of second-order uncertainty that refers to the interval around a best-estimate value, which is typically the average. The interval designates a 90% probability that the actual value lies within the range defined by the boundaries of the interval. The actual top and bottom boundaries of the interval are designated as the 95% and 5% probabilities, respectively.
discount rate	The annual rate at which the calculated future costs and benefits of climate change are reduced per year to define their value in the present.
endogenous	Any quantity that is internally calculated within a computational model.
exceedance probability	A term used to describe the uncertainty. An exceedance probability, which can range from 0% to 100%, indicates the likelihood (or chance) that a particular consequence of climate change will exceed (be greater than) the value reported for that probability. For example, a 25% exceedance probability means there is an estimated 25% chance an impact will exceed the indicated value (in dollars or other quantity) associated with that percentage of impact.

Concept or Term	Meaning
exogenous	Any quantity that is externally provided to a computational model.
frequency	A reflection of how often a condition occurs, for example, how often there is a rain storm that exceeds a specified amount of precipitation, or how often there is a heat wave that exceeds a specified temperature.
"from 2010 to 2050"	The 40-year period covered by the study. This term is inclusive in that both 2010 and 2050 are considered part of the period. Other forms also express this period such as "between 2010 and 2050" and "2010–2050."
intensity	A reflection of quantity over a short period of time, for example, the inches of rain in a single storm or in a single hour, or the maximum temperature during a heat wave.
labor year	A unit of measure equivalent to having a full-time job for a year.
precipitation	Any form of water transferring from the atmosphere to the ground, including rain, snow, sleet, and hail.
referent	A baseline data set with which comparisons of future conditions or impacts can be made. There are four referents used in this report: • **climate referent**: An assumed constant future of climatic conditions that is identical to the average historical values, that is, climate in the absence of climate change. • **macroeconomic referent:** The base-case REMI forecast as based on the Department of Commerce forecast and assuming no future climate change. • **hydrological referent**: The water availability into the future based on the historical supply of surface water and forecast ground-water use compared to implied water demand based on the macroeconomic referent. • **motif**: A fixed pattern used in all the exceedance-probability simulations portraying a representative relationship between precipitation and temperature and their associated frequency and intensity across all the years from 2010 to 2050.
risk	In its specific use for this study, consists of the product of the probability that a certain set of climatic conditions will occur

Concept or Term	Meaning
	times the consequence (or impact) that these conditions will have. Risk reported on a national level as the “summary risk” or "total risk” is the sum of the risk over all possible conditions.
run	In its specific use for this study, denotes any one of the 53 sets of results contained in the PCMDI database that were produced by running any one of 24 climate-change models for the A1B scenario.
scenario	In its specific use for this study, denotes the IPCC A1B Scenario as defined in the Special Report on Emissions Scenarios (Nakicenovic et al. 2000).
second-order uncertainty	The uncertainty in the estimate of uncertainty for a specified variable, such as cost or precipitation.
simulation	In its specific use for this study, denotes the analysis process that proceeds from ascertaining climatic conditions for a given exceedance probability onto a hydrological analysis, followed by the determination of macroeconomic impacts.
uncertainty	A probabilistic measure for the lack of knowledge about the value of a variable, such as cost or precipitation.
water availability	The ratio of the supply of water compared to the indicated demand for water. The indicated demand is that demand associated with the macroeconomic referent.

1.2 Relationship to Previous Work

Many research efforts have addressed the uncertainty in climate-change projections (Roe and Baker 2007; Ramanathan and Feng 2008; Murphy et al. 2004). Because of the extensive resource requirements for running simulations of detailed AOCGMs, most of these analyses were performed on individual, often simplified, models. It is not uncommon for a full-blown model to take months of computer time to produce results over a long time frame. The PCMDI data set used in our study consists of the results from the 24 most accepted climate models. To assess the risk of climate change, we use these results as an ensemble (Palmer 2002). For the most part, the uncertainty within a particular model is *less* than the uncertainty across all the models (Giorgi and Francisco 2000). For risk assessment, the inferred uncertainty across the ensemble of models, as explained more fully in Section 3.1.1, is then deemed appropriate (Tebaldi and Knutti 2007), even for precipitation and hydrological assessments (Backlund et al. 2008), and therefore is used in the study reported here.

Several studies have combined macroeconomic analyses with climate models to conduct sensitivity analyses on the data, but the focus of these studies was largely to determine the sensitivity associated with forecasting uncertain GHG emissions (Webster et al. 2003; Stott and Forest 2007; Prinn et al. 1999; Sokolov et al. 2009). Webster et al. (2003) note the need to include uncertainty quantification for decision making in regard to climate change.

The cost associated with climate change is routinely cast in the context of the cost to mitigate climate change (Barker et al. 2006; Schaeffer et al. 2008). This perspective is the context of the IPCC integrated assessments (IPCC 2007b) and that of many other researchers (IPCC 2007a). In this study, we do not consider the responses or cost of mitigation. Other studies consider risk assessment for adaptation (see Alkhaled et al. [2007] for a review) but not as part of a macroeconomic response. A recent study (Parry et al. 2009) argues that the cost of adaptation is significantly underestimated. The consulting firm of McKinsey (2009) produced a detailed set of case studies to determine the adaptation cost from a bottom-up perspective that goes well beyond the technology detail of our study. Their study, like ours, strives to inform the decision-making process for responses to climate change. The McKinsey work is limited to the direct cost under an aggressive implementation of technologies. Although our study only considers a few representative technological responses to reduced water availability, it follows the dynamics of both the direct and indirect flows of impacts through the economy.

Additionally, many studies have addressed the impacts of climate change, often at a global resolution (Tol 2002a, 2009). A few studies include regional analyses that contain the United States. The IPCC does consider the U.S. ecological and physical impacts of climate change but does not quantify risk (Field et al. 2007). The most visibly noted regional analyses are those of Nordhaus via his RICE model (Nordhaus and Yang 1996; Nordhaus 2006) and of Stern (2008) via the PAGE2002 model (Hope 2006). The Nordhaus model is a clairvoyant optimization model that uses a much higher discount rate than the discount rated used in *The Economics of Climate Change: The Stern Review* (discussed below). While less detailed in its analysis, the Stern Review (Stern 2007) is the most comparable to our study.

There are also studies that consider the cost or physical impacts for particular states and regions within the United States and, in particular, use hydrology as the conveyer of the impacts (Vicuna et al. 2009; Christensen et al. 2004; Frei et al. 2002; Chang 2003; Jha et al. 2004; Hayhoe et al. 2004; Dettinger et al. 2004; Frederick and Schwarz 1999; Chen et al. 2001; NAST 2001; Stone et al. 2001; Mauer and Duffy 2005; Leung et al. 2004; Mastrandrea et al. 2009; State of New Mexico 2005; Ruth et al. 2007). Mastrandrea et al. (2009) also consider impacts across economic sectors down to the county level for California. Our study examines all of the individual lower-48 states including the District of Columbia with their economic sectors interacting in response to the impacts of climate change. A recent study by Karl et al. (2009) considers the regional impacts of climate change over the entire United States, but their discussion is largely qualitative and not conducted from the perspective of quantitative risk analysis. Parry et al. (2009) note that the overall impacts of climate change (at a global level) may be significantly larger than previously estimated. Both the IPCC (2007b) and Tol (2002a) provide an overview of the many efforts of forecasting the impact of climate change on natural and social systems.

1.2.1 Impact Studies

Our study generates U.S. GDP impacts in 2050 that are comparable to the impacts determined in the Stern Review (Stern 2007): an average expected loss of approximately 0.1% of the GDP, with a 5% chance the loss will exceed approximately 0.2% of the GDP (Hope and Alberth 2007). The Stern Review, however, includes noneconomic losses that are not contained in our study. Mendelsohn et al. (2000) considered global impacts that include the United States as a studied region, but these researchers derived a positive 0.1% impact on the GDP within the 2050 time frame. Previous analyses, including the Stern Review, have relatively simple damage functions (defined in Section 1.2.2) that primarily capture only the direct impacts. The use of combined industry-level econometric and input-output methods, as applied in our study, highlights the effects of economic multipliers that capture added indirect impacts as damages flow through the economy to suppliers and employees. Importantly, the indirect impacts are typically two to five times larger than the direct impacts.

The impacts of climate change have a large behavioral component. Consumers and industry will respond to impacts, as they occur, to control the consequences to individuals or companies, but with an associated cost. The cost to accommodate climate change is part and parcel of the realistic response to climate change. We contend that climate impacts, and the adjustment to them, are inseparable within a realistic analysis. Nonetheless, studies that consider the impacts in the absence of adaptive responses to them show a GDP loss of 0.4% by 2050, growing to a GDP loss of 1.73% by 2100 (Ackerman et al. 2008). Ackerman et al. (2009) determined a GDP loss of 2.6% in 2100 that has a 17% likelihood of occurrence. Tol and Fankhauser (1998) present the issues associated with the self-consistency between cost (mostly in the domain of mitigation) and adaptation (often limited to improvements in energy usage). Yohe et al. (2007) provide an overview of damage and vulnerability analyses.

Ackerman et al. (2008) base their analysis on the Hope and Alberth (2007) study. Both studies present the 95% uncertainty confidence intervals on their analysis and thus allow a comparison to the results in our analysis.

Several researchers have considered the issues associated with the risk assessment of climate-change precipitation uncertainty at the regional level (New et al. 2007). Others have considered the historical impact of precipitation variability as it applies to future climate change (Seager et al. 2008).

1.2.2 Damage Functions

Analyses of the cost of climate change typically use equations collectively referred to as the *damage function*. These equations are often linear, quadratic, or allometric functions of temperature (Tol 1995, 2002b; Ackerman and Finlayson 2006; Lempert et al. 1996; Roughgarden and Schneider 1999; Ortiz and Markandya 2009). Occasionally, researchers use multiple equations to estimate the climate-change cost impacts for specific sectors (Mendelsohn et al. 2000). Determining the input values for parameters in model equations can be an enumerative process, where researchers use specific cost studies, such as the cost to build sea walls to mitigate rising sea level, to estimate the overall damage cost (Tol 2002a). Sometimes premodeling is required, where separate analyses are used to determine the values for the parameters in those equations. Another approach is the statistical process where researchers use estimates based on comparing variations in costs across countries and time as climatic conditions change (Nordhaus 2006).

We use a combined approach that employs engineering studies to estimate the cost of physically modifying facilities to accommodate new climatic conditions as well as to use the statistically based knowledge of macroeconomic interactions within and across economic sectors (Ackerman et al. 2008). A discussion of the engineering basis of this study is contained in Appendix B. The statistical basis is described in the REMI macroeconomic model documentation (REMI 2007).

Whereas previous studies on the impacts of climate change generally focus on change in temperature (Tol and Fankhauser 1998; Hope and Alberth 2007; Nordhaus and Yang 1996) as the primary uncertainty to the cost of climate change, we only consider temperature as a condition that is associated with the pattern of precipitation over time.

O'Brien et al. (2004) show that what happens within the parts of a country, referred to as "intracountry heterogeneity," better delineates the economic impacts of climate change than analyzing a country as if it were a single homogenous unit. In our study, we examine the impacts at an interacting state level to explore this concern.

1.3 Impact Valuation and the Discount Rate

Economic studies often use discount rates to (1) capture the ability to better accommodate adverse situations in the future because of greater access to resources or (2) recognize that adversity in the present has a greater impact on human decision making than those threats that are still in a distant future. Because of the current controversy surrounding the use of different discount rates to assess the economic impacts of climate change (Nordhaus 2007a), this study estimates the impacts using three discount rates: 0% per year, 1.5% per year, and 3.0% per year. The 1.5% rate roughly corresponds to the rate used in the Stern Review (Stern 2007). Other authors make a strong case for a 0% rate (Dasgupta et al. 1999; Posner 2004), whereas the 3% rate more closely conforms to historical orthodoxy (or conventional practices) in economic analyses (EPA 2000; OMB 2008). A more complete discussion of the various ways to consider discounting is presented in Guo et al. (2006).

If the quantity is, for example, the change in the GDP, then an argument can be made to reduce the net present value of the future impact by the discount rate. The discount rate applies to monetary conditions. Generally, a discount rate is not applied to physical conditions such as human suffering. Analyses for determining the value of public investments often use the discount rate determined in OMB Circular 94 (OMB 2008).

These values apply solely to public works projects and are not used in long-term more-general risk analyses. Nonetheless, the discount rate for long-term projects is consistent with a 3% real discount rate.

The discount rate assumed in climate studies is often based on the discount rate defined by Ramsey or some minor variant thereof (Tol 2009; Nordhaus and Boyer 2000; Stern 2007). The social discount rate, r (Ramsey 1928), as used in such climate analyses (Ackerman et al. 2008; Stern 2007), is represented by Equation (1-1):

$$r = p + \theta * g. \tag{1-1}$$

Here, r is the social discount rate, p is the pure rate of time preference (PRTP), θ is the income elasticity of the marginal utility of consumption (usually assumed to be unity—Cowell and Gardiner 1999; OXERA 2002; Ha-Duong and Treich 2004), and g is the growth rate in per capita consumption. The social discount rate is routinely noted as the time preference or, simply, the discount rate. Note that if the expected economic growth rate was negative, the discount rate could become negative (Dasgupta et al. 1999). Several authors argue that the PRTP should be 0.0 in those instances where an investment is *not* made today to accommodate future conditions (Broome 1992; Cline 1992, 2004). The Stern Review uses a near-zero PRTP, arguing for intergenerational equity and the risk of climate catastrophes (Stern 2007; Sterner and Persson 2008; Nordhaus 2007a).

Several studies indicate the value of θ is in the range of unity or more; however, no value has a solid basis from the data (Buchholtz and Schumacher 2008). Saelen et al. (2008) provide a broad discussion of the debate on the value of the consumption term, θ. Cline (1992) provides a relatively complete derivation of Equation (1-1), but Cline's derivation is based on an absolute (or additive) measure of cost. With precipitation as the primary uncertainty, the damage cost is proportional to the size of the economy, and the justification for θ in Equation (1-1) may be absent. The case for disregarding θ is presented in Appendix G.

There is a difference between a cost analysis that is used to determine the value of mitigation (e.g., Nordhaus 2007b) and the study here. We are solely concerned with the impact of inaction today on deprivation in the future, and we focus on the monetary and employment losses to individuals experiencing them at the future time. Our cost analysis is not associated with the value of an investment today to compensate for the damage cost. How the current society may want to respond to the cost, by preventing it from occurring or by direct financial compensation, is then in the realm of conventional discounting. That analysis is not part of this study. In the sense of divorcing the impacts on future individuals from the impacts on the present, our exercise starts with the ethical basis of the cost to those who will experience it. Broome (1992) notes that the social discount rate within this perspective should be zero—though it can be a positive value when deciding how to accommodate the cost. Davidson (2006) notes that in weighting the investments from the damage maker for compensating the lost consumption of the damage bearer, the discount rate corresponds to the interest rate (typically less than 3%). However, from a regulatory and legal perspective, Davidson argues that the consumption rate of interest is zero (the second term in Equation [1-1]), and therefore the social discount rate for establishing the value to future generations is a PRTP of less than 1% and close to zero. Weisbach and Sunstein (2008) detail the various legal arguments of this debate.

In contrast to the rationale for a near-zero discount rate, climate-change analyses routinely use a discount rate of 3% or greater (Nordhaus and Boyer 2000), whereas Stern (2007) and Cline (2002) used a rate of approximately 1.5%. To be inclusive, Tol (2009) used a range from 0% to 3%, but noted that these rates are the PRTP (pure rate of time preference). We assume the range noted by Tol, but apply his rates for discounting impacts as if these rates represent actual social discount rates. To limit the amount of information presented in this report, and when space warrants only a single example of the analyzed impacts, the values noted in this report reflect a 0% discount rate.

The costs developed in this study only reflect the near-term cost of climate change and do not reflect the accelerating risk from future climate change (Hope and Alberth 2007). The reported damage estimate is the overall actuarial cost of climate change. The cost corresponds to the payout for an insurance policy and hence captures the value society places on avoiding a risk (Weitzman 2009). Conversely, the cost does not fall on the whole society but on a small subset of individuals who pay dearly in the proportional sense (IPCC 2007d). Alfred Marshall (1890) pointed out that an ordinary individual perceives a given cost much more heavily than does a rich individual. Therefore, casting a $1.2 trillion impact, as we have calculated in this study for the loss in the GDP at a 0% discount rate, in the context of a percentage of total economic activity over the time period distorts the actual implications for those who locally experience the loss. Further, when taken in isolation, the value can give a false comfort in disregarding post-2050 impacts. The impacts increase rapidly in the end years of our analysis. If we had continued our analyses further into the future, the reported cost would be much larger than the cost reported herein.

Lastly, because this study considers the cost to the economy from the perspective of those experiencing the impacts at the future time, and because there is no attempt to define mitigation or other policies in the present that would limit those impacts, the 0% discount rate is used as a point of neutrality. We are simply reporting the predicted future cost of climate change in the accounting sense. How the society of the present values the cost from a liability or preference perspective falls in the conventional realm of financial or social discounting—appropriately using a discount rate in excess of zero.

1.4 Document Overview

Section 1 has discussed the perspectives from which climate-change studies have been conducted in the past and pointed out how our study fits within the framework of the literature on climate change. In Section 2, we explain why we have chosen precipitation as the critical component for assessing the impacts of climate change, describe the relationship between uncertainty and risk, and define the means by which we assess and calculate the risk of climate change based on the different levels (and types) of uncertainty. Also included in Section 2 is a statement of inclusions and omissions in the analysis that may have resulted in producing estimates of impacts that are larger or smaller than the impacts that may actually occur. Section 3 details the multistep analysis process we follow to (a) sample data from the indicated uncertainty distribution of an IPCC climate-model ensemble, (b) determine water availability and agricultural production for these future conditions via the hydrological model, and (c) calculate the national and state economic consequences of the hydrological conditions using the REMI model. Section 4 presents the results of our analysis. In Section 5, we summarize key aspects of the analysis process and results and also address issues involved in conducting uncertainty analyses for the risk assessment of climate change. Following Section 5 is a list of references cited in the body of the report.

The appendices supplement information presented in the body of the report, with each appendix having its own succeeding list of references. Appendix A gives an overview of the components of the hydrological model and addresses how the demand for water and the supply of water are calculated. Appendix B provides a detailed explanation of the economic methodology by which hydrological changes are translated into direct economic impacts for input into the REMI model to estimate the economic impacts over the 40-year period. Water shortages are predicted to occur in the United States over the analysis time frame even in the absence of climate change. The impacts resulting from these shortages are not reflected in the reported impacts from climate change but are provided in Appendix C for completeness. Similarly, Appendix D presents estimated values for the salient data from the REMI base-case forecast, our macroeconomic referent, over the 40-year period in the absence of climate change. Appendix E provides detailed national and state information at the 1% exceedance probability for a more in-depth look at the impacts and their volatility by state and industry over time. Appendix F supports the discussion in Section 2.5 related to calculating risk at very high and very low exceedance probabilities. Appendix G contains a discussion of the discount rates when the damage cost varies proportionally with changes in climatic conditions.

2 Uncertainty and Confidence

Rather than applying temperature changes to determine the impacts of climate change, we apply the highly uncertain changes in precipitation along with its volatility to predict the effects on economic activity and interstate human and business migration between 2010 and 2050. We use the U.S. county-level hydrological model developed at Sandia National Laboratories (Sandia) and the PI+ version of the macroeconomic model from REMI (Regional Economic Models Incorporated) configured for 70 economic sectors and for all 50 interacting states. We map each of the 53 PCMDI SRES A1B runs that include precipitation predictions to the CONUS (continental United States) county and state levels so that these runs are compatible with the hydrological and macroeconomic models, respectively. Because Alaska and Hawaii experience different climatic and economic dynamics than CONUS, our analysis of climate-induced risk emphasizes CONUS state-level impacts. Note that both the Sandia hydrological model and the REMI model have been used in the policy arena. In addition, the REMI model is widely used by state governments and corporations. Its forecast is based on the Department of Commerce's official macroeconomic forecast (REMI 2007).

An analysis of the risk from climate change must directly address the uncertainty surrounding that risk. The usefulness of a risk assessment, however, depends on the confidence in the process of its construction. The topics covered in Section 2 describe the issues associated with handling uncertainty and how these issues are addressed. In Section 2.1, we discuss how precipitation uncertainty is used. Section 2.2 explains how uncertainty applies to the calculation of risk, with a description of the approach used in the risk assessment presented in Section 2.3. Section 2.4 addresses our consideration of second-order uncertainty in estimating the impacts of climate change. Recognizing that the extremes of any probabilistic distribution can impact the reported results, we describe in Section 2.5 the mathematical techniques employed to ensure that our approach to assessing risk across the entire distribution is justified. Section 2.6 identifies the salient features included in and omitted from the analysis and states how the omission and inclusion of particular topics may alter the reported results in this study. In Section 2.7, we point out how continuity is maintained in the transition from the realized present to the probabilistic future.

2.1 Precipitation Characterization and Uncertainty

Precipitation is one of the most uncertain aspects within existing climate models. In scenario analyses for policy and planning, the most uncertain characteristic of the future with potentially the greatest consequences is generally selected as the pivotal component of the assessment process (van der Heijden 2005; Ringland 2006; Wilkinson 1995). We use this logic as justification for considering the currently poorly quantified uncertainty in precipitation as the primary driver of the risk assessment in this study. Best estimates are routinely used as the basis for policy assessment, such as the estimates of line-item expenses in the federal budget. Policy assessment requires risk-assessment approaches when there are low-probability events with unacceptable consequences, such as for vaccination regimes to prevent epidemics and for preparedness against earthquakes. Risk assessment requires an understanding of the probabilities that harmful conditions will occur. These probabilities are often not adequately known, and assessments must rely on uncertainty quantification using computerized simulations of future events as we do in this study. Several researchers have noted the need to confront policy assessment with the use of risk assessment based on the uncertainty embodied in simulation ensembles (Palmer 2002; Räisänen and Palmer 2001). The ensembles capture a range of possible outcomes and are a pragmatic proxy for representing the probability of future conditions. Researchers have explored methods to incorporate all the ensemble information in as constructive a manner as possible (Stainforth et al. 2007b; Box and Draper 1987).

Our analysis highlights the climate risk associated with enduring, reduced precipitation within CONUS. Although increased flooding (Milly et al. 2005) and changes in winter versus summer precipitation (NAST 2001) will have impacts, it is unclear how to assign the cost of these conditions to climate change. Changing demographics (Trenberth 2008) and economic growth cause increased damage from extreme weather even in the absence of climate change. Moreover, water management by local councils and state governments to accommodate increased growth tends to further burden existing infrastructure, making the areas more sensitive to adverse weather conditions and producing consequences that mimic those of climate change. While we do associate the impact costs of reduced-precipitation simulations with the temperature-related impacts, we do not include the impact costs of flooding in this analysis. Other studies have addressed the costs of flooding from climate change (McKinsey 2009), and the costs of flooding are typically less substantial than the costs we have estimated for reduced precipitation. Changes in climate-induced precipitation are recognized potentially to cause large impacts (NAST 2001).

We use the range of the projected national precipitation from the PCMDI ensemble over the years 2010 to 2050 as the uncertainty metric. We sample the probability distribution of precipitation based on the ensemble of model runs and adjust the precipitation in each U.S. state in each year between 2010 and 2050 for the implied reduction (or increase). A detailed AOCGM forecast defines the relationship between precipitation and temperature and their respective frequency and intensity. Intensity is a statement about a quantity over a short period of time, for example, the inches of rain in a single storm or in a single hour, or the maximum temperature during a heat wave. Frequency, on the other hand, denotes how often a condition occurs, for example, how often there is a rainstorm that exceeds a specified amount of precipitation, or how often there is a heat wave that exceeds a specified temperature.

As used in this study, the word “sample” is not meant to imply a random process for statistical analysis. The sampling is a purposeful progression to cover the input uncertainty range in a manner that ensures the analysis produces enough results all along the output probability distribution to estimate the risk distribution adequately. The input uncertainty range covers the full set of exceedance probabilities from 0% to 100%. The term “input” defines the information the model needs to perform the analysis, while the term “output signifies the results of the analysis. Associated with these probabilities is the range of possible precipitation, from the minimum amount of precipitation (in inches per year) at a 0% exceedance probability to the maximum amount of precipitation at a 100%

exceedance probability. The amount of precipitation varies significantly from state to state. An exceedance probability is the probability that the actual value of a quantity, such as the extent of a drought or the loss of the GDP, will exceed the stated value. The concept of "exceed" can also express a diminishing value. The exceedance probability on precipitation designates the probability the precipitation will be lower than stated. Sections 2.3, 2.4, and 2.5 explain our use of exceedance probabilities in further detail.

We have not attempted to characterize the full spectrum of the weather-frequency and weather-intensity uncertainty projected by the AOGCMs as a consequence of climate change. Instead, we use a specific pattern, called the *motif*, which relates precipitation, temperature, frequency, and intensity across all the simulations we run to estimate the probabilistic impacts of climate change on the U.S. economy. An in-depth examination of the motif appears in Section 3.

2.2 Uncertainty Means Greater Risk

The focus of a scientific endeavor is to improve confidence in the validity of conclusions drawn from data and analysis. Risk, on the other hand, is concerned with the opposite position. In this case, what is the chance that scientifically conservative estimates of climate change are actually optimistic? Consequently, our study emphasizes tails of the climatic (e.g., precipitation) distribution rather than the most likely part of the distribution that is generally of most concern to scientists and policy makers. We concentrate particularly on the tail of the distribution in which there are small probabilities *but realizable risks* that the effects and consequences of climate change could be much more severe than predicted from the best estimates.

Uncertainly is most commonly represented via a probability density function, which is sometimes simply called a "probability distribution." From a statistical perspective, the probability density function captures the idea of how often a given value can be expected to occur in comparison with other values. When the uncertainty increases, there is more of a chance that a variable, such as the local rise in temperature, will have a value different from the value that occurs most often, called the *mode*. The mode is the peak of the distribution.

Figure 2-1 conceptually illustrates two probability distribution functions with the same mode (i.e., location of the peak value) where the blue-line distribution has greater uncertainty than the red-line distribution. The left (y) axis shows the measure of probability, and the lower (x) axis shows the increased delta (Δ) change in average temperature compared to a world without climate change. The blue line is above the red line in the right-side tail of the distribution. Extreme levels are defined as those conditions well removed from the mode of the distribution, for example, changes in temperature of over 5 degrees in Figures 2-1 and 2-2. Thus, there is a greater chance of the temperature occuring at extreme levels with the blue-line distribution. Figure 2-2 provides the same logic as Figure 2-1 when there is a greater concern with the average value (or *mean*) of the distribution than with the mode.

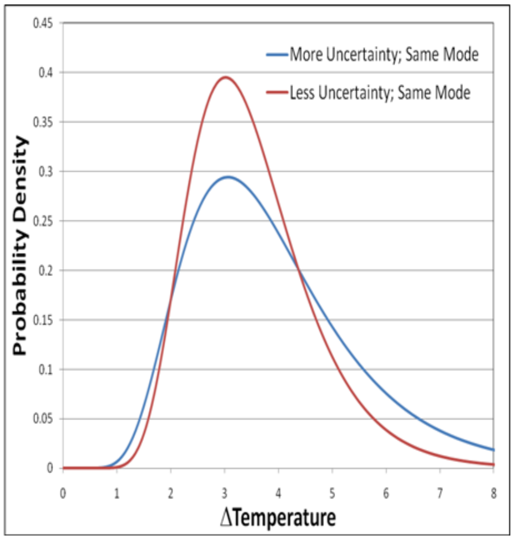

Figure 2-1. Probability distribution with constant mode.

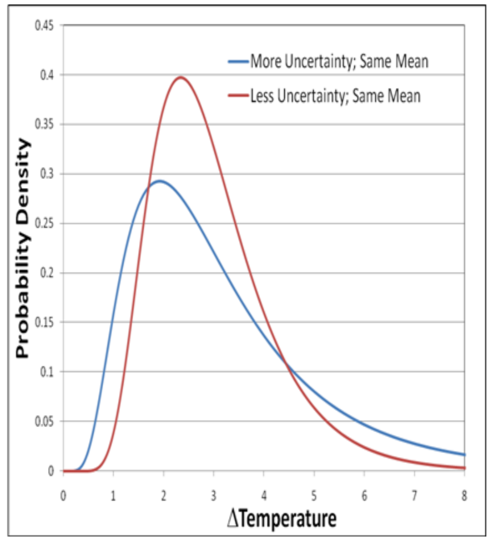

Figure 2-2. Probability distribution with constant mean.

In risk assessment, a useful perspective contains the cumulative distribution function (CDF). A CDF transforms the probability distribution, such as those above, to show the probabilities of exceeding the values of concern. For purposes of this study, we refer to these cumulative probabilities as "exceedance probabilities." A CDF shows the probability starting at a 0% exceedance probability on the left side of a graph and increasing to the right toward 100%. A complementary cumulative distribution function (CCDF) is the reverse of a CDF. The CCDF is one (1.0) minus the CDF. It starts with the 100% exceedance probability on the left side and drops toward the 0% exceedance probability. Both CDFs and CCDFs are commonly used for presenting the uncertainty in climate change (Knutti et al. 2008) and for assessing the risks from climate change (Schneider and Mastrandrea 2005; Mastrandrea and Schneider 2004).

Figure 2-3 is the CCDF associated with Figure 2-2. The lines in Figure 2-3 cross at the median of the distribution. The median is the point where there is an equal probability that the value, in this case the change in temperature, will be greater than or less than the value at the 50% exceedance probability. With skewed probability distributions, such as those associated with climate change, the mode, mean, and median take on separate values. For a symmetric probability distribution like a bell curve, which has equal tails on each side of the mode, the mode, mean and median all have the same value. For the skewed probability distribution associated with the blue curve of Figure 2-2, the mode is to the far left at approximately 2 degrees, the median is slightly to the right of the mode at approximately 2.5 degrees, and the mean or average is at approximately 3 degrees.

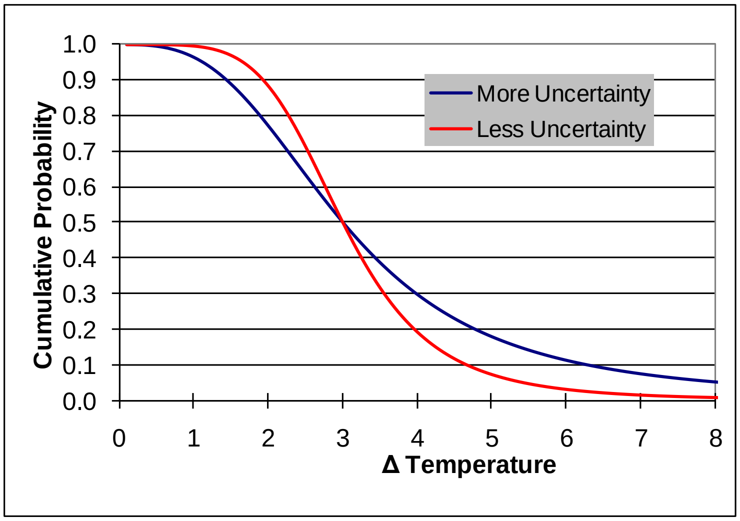

Figure 2-3. A CCDF (complementary cumulative probability function) with uncertainty.

Figure 2-3 illustrates the probability that the high-temperature deltas associated with climate change are greater when there is a greater level of uncertainty. For instance, in the "red-line" lesser-uncertainty curve, the chance of exceeding a temperature of 6 degrees is approximately 2%, whereas for the "blue-line" greater-uncertainty curve, the risk of exceeding 6 degrees is approximately 11%. Further, the more uncertain blue line appears not to produce a 2% exceedance probability to well beyond 8 degrees, possibly not until a daunting 12 degrees, in this purely illustrative example. If the consequence of climate change also increases with temperature, the risk (the consequence multiplied by the probability) remains significant even at extreme conditions. Thus, the greater the uncertainty, the greater the risk.

2.3 Risk Assessment

We use the approach proposed by Kaplan and Garrick (1981) to quantify risk. Basically, risk is defined in terms of answers to three questions: (1) What can happen? (2) How likely is it to happen? and (3) If it does happen, what is the consequence? The "what" response to question one refers to the climate-change conditions at a stated exceedance probability. Question two is the probability, p, as defined by the exceedance probability, that those climatic conditions will occur. Question three addresses the consequence of the climatic conditions at the stated exceedance probability, which is determined by first developing the hydrological consequence of the climatic conditions on water availability followed by the socioeconomic consequence on economic activity and demographics.

In a simulated situation, Helton (1994) calculated the risk as the sum of the consequence, C, for a probability interval multiplied by the range of the probability interval, ΔP, associated with that consequence over all the simulations of exceedance probabilities, n, over time, t.

$$Risk = \sum_t \sum_n C(n,t) * \Delta P(n). \qquad (2\text{-}1)$$

Equation 2-1 can be thought of in terms, for instance, of the consequence of events that occur with a 10% to 12% chance (the probability interval). The risk is the sum over all the intervals needed to cover 0% to 100% over the years 2010 through 2050. Equation 2-1 is actually a calculation of total risk. In the situation of a financial cost, the discounted risk, using a discount rate, *r*, is then

$$Risk = \sum_t \sum_n C(n,t) * \Delta P(n) / (1+r)^2. \qquad (2\text{-}2)$$

The integrated-risk impact on demographics, for example, as measured for socioeconomic conditions such as unemployment or population migration, is not directly a financial quantity and therefore is not discounted over time. The integral is the summation of Equation (2-2) when the probability intervals (the ΔPs) become infinitesimally small and, as a result, explicitly include all possible consequences and associated probabilities. In simpler terms, risk in this study is the sum of the consequences calculated for the range of the exceedance probabilities simulated.

Figure 2-4 adds an illustrative (green) consequence curve to Figure 2-1 to help demonstrate how uncertainty affects risk. The consequence curve is expressed in units of trillions of dollars and uses the same numerical values on the left-hand side of the graph, e.g., a probability-density value of 0.05 is equivalent to $0.05 trillion or $50 billion. The consequence curve depicts how the cost rises as temperature increases. Thus, for example, the consequence at 5 degrees is approximately $25 billion, while at 7 degrees the consequence is $170 billion.

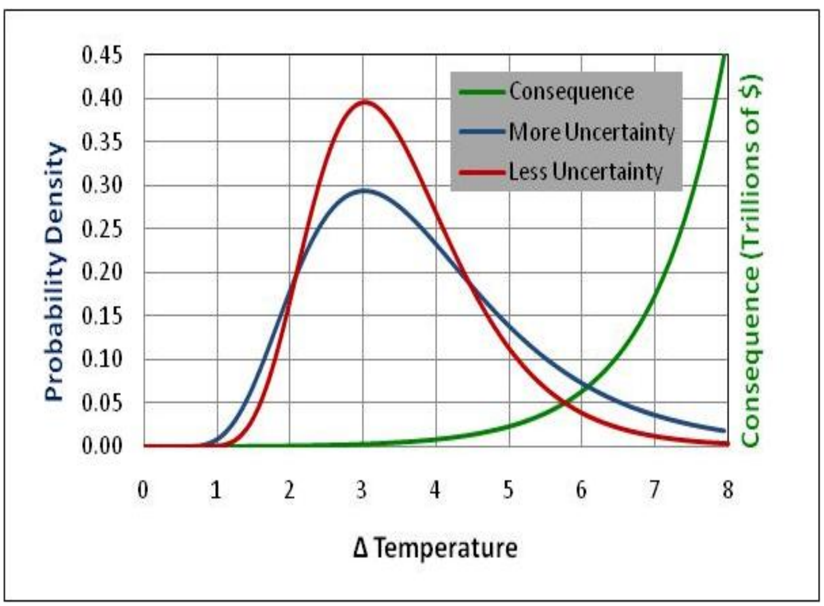

Figure 2-4. Probability and consequence

Equation (2-1) combines the probability and consequences shown in Figure 2-4 to calculate the risk. Figure 2-5 shows how the illustrative risk grows as the summing process of Equation (2-1) contains more of the temperature range. In this figure, the y-axis represents the cumulative risk only, in billions of dollars.

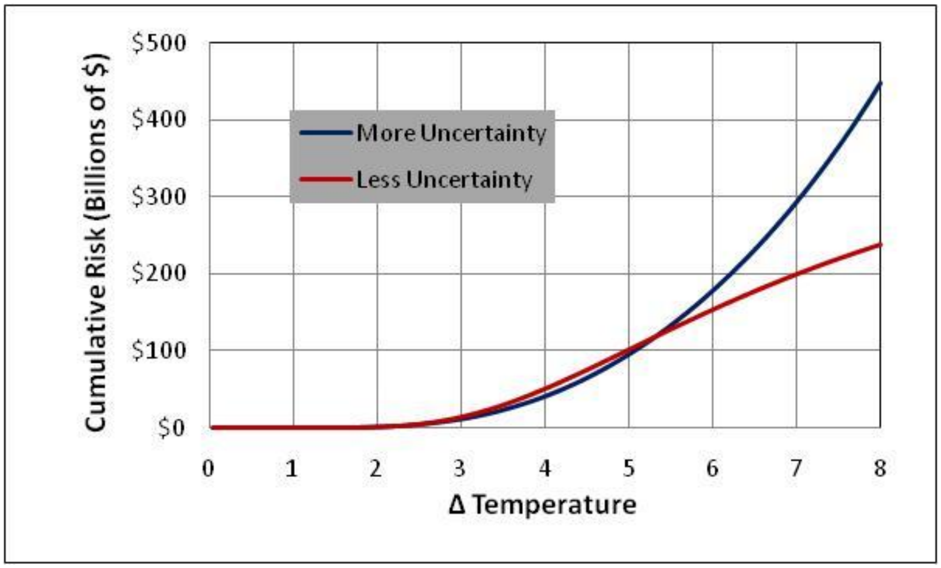

Figure 2-5. Probability and risk.

In Figure 2-5, for example, at 5.5 degrees where the two risk curves for different levels of uncertainty cross, the risk for both curves is the same at roughly $120 billion. Beyond this point, however, the risk diverges. By 7 degrees, the value of the risk with less uncertainty (red curve) has risen to $200 billion, and the value of the risk with more uncertainty (blue curve) has risen to $300 billion. The higher levels of the probability density for the blue curve compared to the red curve, for example at 6 degrees, contribute heavily to the overall higher risk of the blue curve, as depicted in Figure 2-5. By the time the summing process of Equation (2-1) covers 8 degrees, the risk of the blue curve is nearly twice that of the red curve, with the blue curve still rising rapidly and the red curve already flattening out (i.e., becoming a horizontal line) toward what will become a total risk value of nearly $350 billion. On the other hand, in this illustrative example, the blue curve will have a total risk of $1.8 trillion. The lower consequences below 3 degrees, as depicted by the green curve in Figure 2-4, mean that the risk in Figure 2-5 is largely insensitive to uncertainty for lower temperature conditions. This same logic applies for the precipitation focus of our study. Note, however, that with temperature, the larger consequences are associated with higher temperatures; with precipitation, the higher consequences are associated with lower levels of precipitation. Effectively, risk is largely insensitive to uncertainty for higher levels of precipitation, and the cost rises as precipitation decreases.

To assess the socioeconomic consequences of the impact of climate change, we use an econometrically estimated macroeconomic model. To that model, we explicitly add the costs of options for maintaining economic production and population needs under conditions of reduced water availability. Based on the historical response characteristics of the populations, the model internally decides when and how much adaptation to undertake. In this study, adaptation is the act of physically modifying the way installations produce economic output such that they can continue to operate despite changes in climatic conditions. For the purposes of this study, the adaptations specifically act to mitigate the impacts of reduced precipitation. Other studies omit adaptation (Ackerman and Finlayson 2006) or narrowly assume that the only goal of adaptation is to maintain the current socioeconomic conditions. In our work, adaptation covers the activities in which entities (i.e., consumers and industries) engage in the economy to maintain economic viability and hopefully continue to prosper in a changing environment characterized by climate-induced costs that cause further changes in socioeconomic conditions. The outcome will generally be noticeably different from the status quo.

With a fixed amount of water associated with each simulation of possible precipitation, an increase in economic activity would require more than proportional increases in the costs of adaptation. As an example, suppose the water availability from a given simulation was 100 million gallons of water for an economy of $1 billion. A simulation that reduced that amount of water by 50% would result in a shortage of 50 million gallons of water. If the same economy grew to $2 billion, 50 million gallons of water would have to serve that enhanced economy with one-fourth of the amount of water that is needed. Effectively, the enlarged economy would need to cut its water usage back by 75% and would be faced with the costs of reducing water usage to that low level. The additional costs of reducing water consumption by such a large degree could result in the growth rate of economic activity reversing sign and becoming negative as local industries became noncompetitive or as water constraints simply prevented positive economic or demographic growth.

Technological advances might be able, within limits, to reduce water consumption per unit of economic activity with costs to the economy that do not increase in direct proportion to the reduction of water usage. That is, the costs for a factory to reduce water by 50% in 2030 may be $1.2 million but only $1 million to reduce it by 75% in 2050. Nonetheless, for any given level of economic activity at a specified time, the costs to bring the consumption of water back in line with reduced water availability are proportional to the reduction in water availability. Consequently, economic growth would increase the total impact costs in proportion to its effect on the reduced water availability over time. It is the reduction in water availability that would accelerate rapidly with increased economic growth.

Because this study includes simulating the adaptive response of consumers and industries to reduced precipitation, the costs to the economy are typically less than what they would be if the economy was simulated as being rigid and void of adaptation. Analyses that do not have consumers and producers dynamically adapting to climate change quantify what the impacts of climate change would be in the absence of adaptive behaviors. These types of analyses are useful for establishing the immediate direction and scale of impacts but not for quantifying the costs over time in a responsive economy. In both types of analyses (those that assume a rigid response to change and those that assume an adaptive response to change), increased economic growth would result in amplified water-availability problems. These considerations reiterate the point that the larger the economy becomes over time, the larger the impacts of climate change will be on that economy.

2.4 Second-Order Uncertainty

Second-order uncertainty is the uncertainty in the uncertainty. The dashed-line confidence boundaries in Figure 2-6 represent the second-order uncertainty on the values we are reporting in this study. The values we are reporting, as noted by the solid curve in the figure, are the "best estimate" values of the first-order uncertainty. Each of the percentages represents an exceedance probability.

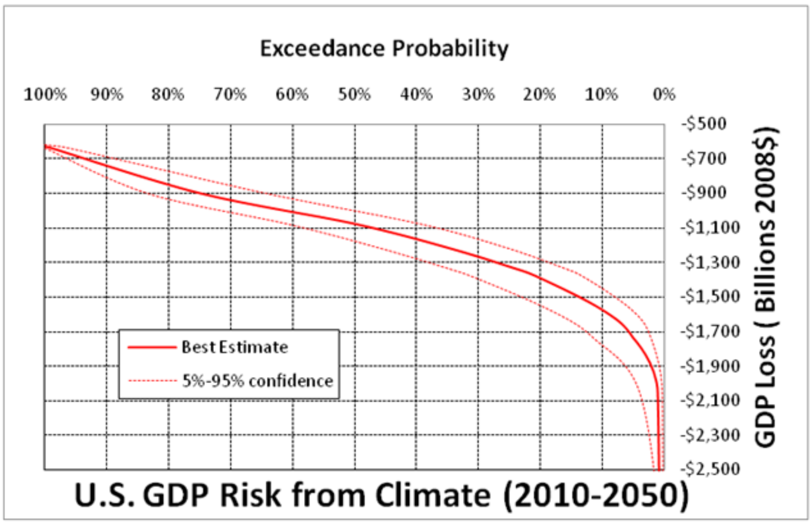

Figure 2-6. Example of second-order uncertainty represented by two dashed lines around "best estimate" solid line.

We derive our first-order and second-order uncertainty distributions by estimating a probability distribution for the precipitation data of the 53 SRES A1B ensemble runs (see Section 3.2). The second-order uncertainty to which we refer was formalized in the *probability frequency* characterization of Kaplan and Garrick (1981). It is the uncertainty on the estimate of the average response of the models in the ensemble. It does not necessarily reflect the uncertainty in actual future climatic conditions over what the simulation results imply as best estimates. Undoubtedly, the ensemble of model runs we use does not even reflect all the uncertainty associated with climate modeling. We use the variation in results across the ensemble as a proxy for climate uncertainty and point out three benefits to using the PCMDI ensemble. First, the ensemble exists and is publicly available. Second, the ensemble is based on the carefully constructed studies for the IPCC. And third, the ensemble reflects a significant degree of epistemic uncertainty (Knutti 2008; Tebaldi and Knutti 2007). The 53 PCMDI results from 24 climate models under the A1B scenario also capture some aleatory uncertainty because of variations in model parameterization, but these variations were not meant to reflect a probabilistic assessment of climatic uncertainty.

Epistemic uncertainty is a type of uncertainty that is due to lack of knowledge or incomplete knowledge. Aleatory uncertainty is typically referred to as simply variability and is commonly used to describe the variability in the collected data used to construct a model and the uncertainty in parameter estimation. In the instance of the ensemble, the different models used reflect epistemic uncertainty in the model structure and in the simulation of physical processes. The ensemble contains some aleatory uncertainty via the use of differing model parameterizations for calibration to match historical observations within several of the models (Tebaldi and Knutti 2007; Knutti 2008; Diegert et al. 2007). Other studies may also be helpful in understanding the representation of uncertainty in model predictions, for example, see Helton and Davis (2002), Helton et al. (2004), Helton et al. (2008), Oberkampf et al. (2004), and Pilch et al. (2006).

From the data contained within the ensemble runs, we can estimate a distribution of, for example, global precipitation over time. That estimate is only an estimate and therefore contains uncertainty. We can use statistics to determine the uncertainty in our estimate of the precipitation distribution. This second estimate of the uncertainty is the second-order uncertainty we use in this study. The second-order uncertainty could become very important on the tail of the distribution where there is a high consequence and where the probability of a condition can be much different from that associated with the mean (average) estimate of the probability. Note in Figure 2-6 that the lower dashed (uncertainty on the uncertainty) curve produces a greater impact than the best estimate at lower exceedance probabilities. For instance, the best-estimate impact at a 5% exceedance probability is a loss of $1,700 billion, whereas the lower (dashed-line) uncertainty loss at a 5% exceedance probability is $2,000 billion. The summary GDP and the employment impacts reported in this study acknowledge this second-order uncertainty, but our emphasis is on the first-order uncertainty to preserve the clarity of the assessment. While we have the ability to address second-order uncertainty, we limit the presentation of this type of uncertainty and instead emphasize the use of the first-order uncertainty for performing risk assessments that integrate climate phenomena, the physical implications for economic activity, and the detailed characterization of socioeconomic impacts. As the pragmatic purpose of this study is to inform decision makers about the near-term risk of climate change, we have purposely kept the complications of presenting second-order uncertainty to a minimum. A detailed incorporation of second-order uncertainty into our analysis would not markedly affect our main conclusions.

2.5 Interpolated Versus Extrapolated Risk

As discussed more fully in subsequent sections of the report, we make the highly uncertain variation in precipitation central to our analysis because this variation has the most direct impact on the also highly uncertain socioeconomic consequences of climate change. We use the gamma distribution to describe the probability density function for precipitation (Groisman et al. 1999). The gamma distribution does not generally look like a bell-shaped distribution but is normally skewed to the right with its left-hand minimum at the origin of the axis and its long tail on the right side extending far beyond the origin. The blue line in Figure 2-2 shown previously approximates the shape of a typical gamma distribution. The statistical analysis of the PCMDI ensemble results for precipitation very closely matches the assumed gamma-distributed precipitation (see Section 3.1). The tip of the distribution's tail could represent unacceptable consequences and generate infinite risks that are impossible to calculate. For our study to be meaningful, we must establish that the risk is finite and therefore potentially manageable through policy intervention.

Many climate studies, such as Nordhaus and Yang (1996) and Hope and Alberth (2007), estimate the costs of the impacts of climate change based solely on change in temperature. The probability density function for the temperature-change distribution is skewed to the right, with a long slowly declining tail for larger changes in temperature (Roe and Baker 2007; Ramanathan and Feng 2008), as is illustrated in Figure 1-1. This tail of increasing temperature is typically the central concern for climate-induced damage. Cost assessments that include ever-increasing human suffering or loss of life are considered unbounded and can have infinite values, that is, they have no upper limit and consequently cannot be calculated (Weitzman 2009).

The *Dismal Theorem* (Weitzman 2009) contends that in the right-hand tail of, for example, the temperature distribution (see Figure 2-2), the consequences of climate change may increase faster than the probability of these consequences declines. That is, consequences increase so rapidly compared to the declining probability that risk (probability multiplied by consequence) continues to rise toward infinite values with increasing temperature.

The primary uncertainty in our study is precipitation, which is bounded on its lower extreme by 0.0 (see Section 3.1.1). This fact forces the precipitation to drop rapidly to zero as the probability goes to 0.0. Further, because this study is only concerned with economic impacts, as opposed to human suffering, the maximum value of the consequences is finite. The worst imaginable loss is the entire economy. We explicitly simulate the consequences between the 99% and 1% exceedance probabilities, assuming that interval captures the largest component of risk. Nonetheless, characterization of the damage function and how the probability goes to zero could still, in principle, dominate the estimate of expected risk.

For the assessment in this study to be useful, the risks associated with the extreme of the tail (below a 1% exceedance probability) that are not simulated must not dominate the total risk. In other words, we must ensure that the uncertainty in estimating the probability distribution function has a limited impact on calculation of the total risk. While we stop the formal analysis at a 1% exceedance probability, we separately extrapolate the results to calculate the impacts between the 1% and 0% exceedance probabilities to determine the magnitude of its contribution to the total risk. For illustration purposes, Figure 2-7 points out the 99% to 1% exceedance-probability interval. The 100% to 99% interval and the 1% to 0% interval reside on either side of it.

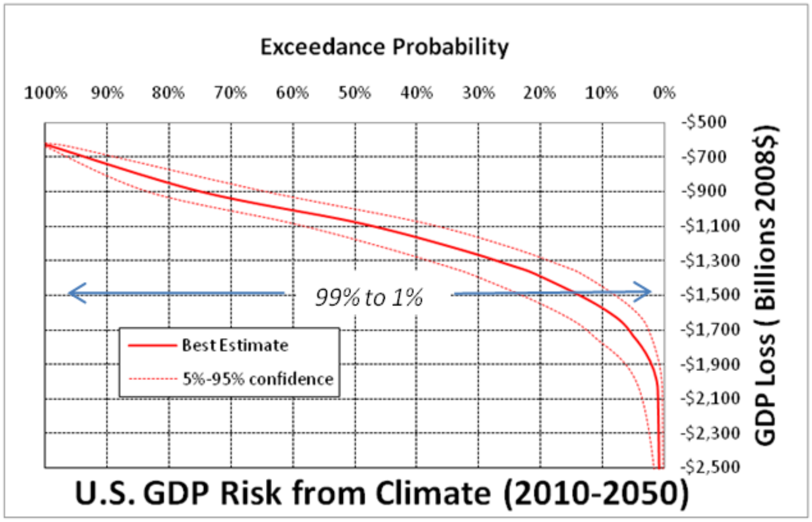

Figure 2-7. Exceedance-probability intervals of interest in methods of risk calculation: 100% to 99%, 99% to 1%, and 1% to 0%.

The estimated summary (or total) risk is the approximate sum of consequence multiplied by the probability, as specified in Equations (2-1) and (2-2). The interpolated values are based on simulated estimates between the 99% and 1% exceedance probabilities. The extrapolated value includes estimates of the contribution to risk between the 100% to 99% exceedance probabilities (the largest amount of precipitation) and between the 1% and 0% exceedance probabilities (very severe drought) encompassed by the distribution.

The impacts from the 100% to 99% probability interval represent simulations with the maximum precipitation justified by the probability distribution. Even in situations where there is abundant water on average, climate change still trends toward reduced precipitation, which still includes both drought and flood conditions. The high-exceedance-probability cases (> 50%) represent conditions where there is more precipitation than is estimated to occur on average with climate change. The predicted climate change is toward drier conditions in the United States on average, on an annual basis. Although flooding could increase in the high-exceedance-probability cases, the estimates we consider account for only those costs associated with the intermittent dry or drought periods that are part and parcel of the climate-change–predicted increases in the frequency and intensity of extreme weather. Because flooding is easier to accommodate than drought with less costs, and these lesser costs are the subject of other studies (Frederick and Schwarz 2000), we do not include the impacts of flooding in the assessment. For example, low-cost approaches to dealing with flooding could be to stop development in flood plains or to modify land elevations for directing excess water flows safely. On the other hand, during long periods of severe drought, a state may find it impossible to maintain economic activity by building enough water storage and collecting all water for what little precipitation does occur. Because increased precipitation simply reduces the frequency and intensity of drought conditions, the estimated impact of drought gradually becomes smaller and smaller at the higher exceedance probabilities. The lessening probabilities of drought, from improving probabilities of precipitation, cause costs to change gradually above the 50% exceedance-probability simulations, and as such, the 100% exceedance-probability values are estimated by simple linear extrapolation. That is, the 100% exceedance-probability conditions are just part of the gradual decrease in impacts due to drought as the average precipitation increases.

The 1% to 0% probability interval is more problematic than the 100% to 99% probability interval. A 0% exceedance probability essentially implies the absence of any natural precipitation. We estimate the consequences of this interval solely to establish that inexact tail contributions to impacts do not dramatically affect the total risk estimate beyond the risk estimated with the interpolation approach. Appendix F describes the calculation of consequences within the 1% to 0% probability interval.

Our calculations indicate the contribution of the 1% to 0% interval to the increase in the summary risk is on the order of 10% greater than the impact estimated over the 99% to 1% interval that is the focus of this study. That is, the formally simulated risk between 99% and 1% represents approximately 90% of the total (i.e., $1.2 trillion) risk. For particular states in this country, the impact could be as high as 25% because local growth rates significantly exceed the national average. The sum of all the interpolated impacts by individual states equals the national impacts. The sum of extrapolated values for individual states does not add up to the national total because the growth in the individual states can each be significantly different from those for the United States as a whole. Thus, there is little chance the extrapolated values for the individual states, with their varied growth rates, would add up to the same value calculated for the extrapolated United States with its single growth rate. The assessment of risk over the entire probability distribution (100% to 0%) of the GDP impacts generates a complete statement of the expected risk for informing policy debates. As described above, the contribution of the extreme 1% to 0% tail does not reverse the risk calculated between the 100% and 1% exceedance probabilities. This fact justifies the use of the detailed analyses between 99% and 1%, along with the extrapolated values, as a basis for portraying the risk from climate change.

2.6 Inclusions and Omissions

A simulation-based impact analysis, explicitly or implicitly, contains limiting assumptions that can bias the results of the analysis. No finite analysis can address all possible features of a real-world system. A simulation necessarily simplifies the actual system it addresses. The simulation and the impact analysis need to contain the salient features that affect the problem being addressed. In this section, we describe what is included in the analysis and what has been omitted from the analysis. These simplifications may result in producing estimates of impacts that are larger or smaller than the impacts that may actually occur. These effects are treated as biases, and they may be deemed optimistic or conservative, depending on the perspective for using the results. In this study, we attempt to balance the optimistic and conservative aspects of the analysis. The elements of damage associated with climate change described below attempt to address the classes of concerns noted by Tol (2002a). Richardson et al. (2009)

note other risks of climate change, many of which do not affect the United States, such as hunger.

Economic Coverage: The analysis captures the interactions and interdependencies among the lower 48 states plus the District of Columbia. The analysis can then reconcile population migration and changes in industry-specific activities across states. We include the economic components noted in Table 2-1. However, we only explicitly simulate the impact of water availability on the following industries:

- Agriculture/farming
- Food
- Beverage
- Paper
- Petroleum and coal
- Chemical
- Primary metal
- Mining
- Thermoelectric power generation
- Hydropower
- Municipal water utilities

Table 2-1. Economic Sector Detail

Forestry and logging; Fishing, hunting, and trapping	Truck transportation; Couriers and messengers
Agriculture and forestry support activities; Other	Transit and ground passenger transportation
Oil and gas extraction	Pipeline transportation
Mining (except oil and gas)	Scenic and sightseeing transportation; support activities
Support activities for mining	Warehousing and storage
Utilities	Publishing industries, except Internet
Construction	Motion picture and sound recording industries
Wood product manufacturing	Internet publishing and broadcasting; ISPs, search portals, and data processing; Other information services
Nonmetallic mineral product manufacturing	Broadcasting, except Internet; Telecommunications
Primary metal manufacturing	Monetary authorities - central bank; Credit intermediation and related activities; Funds, trusts, & other financial vehicles
Fabricated metal product manufacturing	Securities, commodity contracts, investments
Machinery manufacturing	Insurance carriers and related activities
Computer and electronic product manufacturing	Real estate
Electrical equipment and appliance manufacturing	Rental and leasing services; Lessors of nonfinancial intangible assets
Motor vehicles, bodies & trailers, and parts manufacturing	Professional and technical services
Other transportation equipment manufacturing	Management of companies and enterprises
Furniture and related product manufacturing	Administrative and support services
Miscellaneous manufacturing	Waste management and remediation services
Food manufacturing	Educational services
Beverage and tobacco product manufacturing	Ambulatory health care services
Textile mills	Hospitals
Textile product mills	Nursing and residential care facilities
Apparel manufacturing	Social assistance
Leather and allied product manufacturing	Performing arts and spectator sports
Paper manufacturing	Museums, historical sites, zoos, and parks
Printing and related support activities	Amusement, gambling, and recreation
Petroleum and coal product manufacturing	Accommodation
Chemical manufacturing	Food services and drinking places
Plastics and rubber product manufacturing	Repair and maintenance
Wholesale trade	Personal and laundry services
Retail trade	Membership associations and organizations
Air transportation	Private households
Rail transportation	Separate national and state and local government components
Water transportation	Rest of the world imports and exports

The impacts on all other economic sectors are due to interdependencies with the affected sectors. The noted sectors are those with significant water use and sensitivity to water availability. Ignoring the direct impact of water availability on industries with limited dependence on water may slightly underestimate the economic impacts.

Dynamics: Our analysis is dynamic (follows the cause-and-effect responses, year by year) rather than static (an equilibrium result within a set time horizon). The simulated economic decisions are largely myopic rather than clairvoyant. The decisions are based on past behavior patterns rather than on optimal choices. Classical economics may indicate this approach overestimates the economic impacts. Modern behavioral economics may indicate this approach still underestimates the economic impacts.

Extreme Events: We only focus on the variations in precipitation and do include the associated variations in temperature. We do not include additional destructive extreme events such as flooding or wind storms. The impacts of flooding are noted in other studies with expectations of new climate-related damages within the spectrum of historical values (Frederick and Schwarz 2000; Kunkel et al. 1999; Changnon 2003). The lack of consideration of wind damage could underestimate the impacts, but building-design regulations limit the potential for such damage. Because the primary uncertainty used for the risk assessment is based on national precipitation levels mapped to state-specific precipitation with a motif based on a single model, the primary uncertainty may modestly overestimate the reduction in precipitation and the impact in, for example, the central U.S. states. Nonetheless, the damage from destructive extreme events may be very large for low-probability conditions, leading to the possibility that the risk calculated in this study is underestimated.

Water Rights: We assume jurisdictional water rights ensure a distribution of shortages across affected regions rather than having local shortages disproportionally exacerbating downstream conditions. This assumption may underestimate the downstream impacts. On the other hand, we assume that industry and urban areas can purchase available water rights from agriculture and mining users. This assumption may overestimate the impacts on mining and agriculture while underestimating the impacts on urban and industrial areas.

Local Effects: There may be unique local (county-level) effects with much larger intensity than would be indicated in the state-level averages. Local effects may cause aggregate state-level effects to be underestimated. However, over a state, positive and negative effects tend to average out, simply due to the process of aggregation. That is, historical events are equally captured in aggregate data representations, as well as in detailed local data. The climate data only have resolution in excess of 100-kilometer grids, which limits their ability to provide a representative description of the local climate. The hydrological model determines the state-level impact by aggregating county-level considerations. The parameterization of the REMI model builds its state-level configuration by using locale-specific Standard Metropolitan Statistical Area (SMSA) data sets. This bottom-up approach recognizes the relative contributions of various geographic areas to the overall economic activity in each state. With recognition of the limitations from climate-model uncertainty and spatial resolution, the implicit incorporation of local considerations within the hydrological and macroeconomic models would indicate that our aggregate state-level view should have a minimal effect on the overestimation or underestimation of impacts.

Technology: Our analysis attempts to portray the impacts of climate change over the years 2010 to 2050 in the absence of climate-policy initiatives. Autonomous and price-induced technology improvements that already reduce energy use may compensate for what would have been increased cooling loads resulting from climate change (Wilbanks et al. 2008). To keep this analysis focused on a manageable referent-based assessment, we do not include the uncertainty in energy (e.g., oil) prices. Implicitly, we assume that actual primary-energy prices have an upward trend. For energy use, the effects of temperature and technology are assumed to compensate mutually toward no net impact.

Fuel Use: We do include the impacts on energy use by industry due to the loss of cooling or consumptive water if such usage leads to reduced industrial production. We implicitly are concerned about the temperature of the water used in the alternative cooling solutions and reflecting those impacts through changes in cost. As the temperature of the air warms as part of climate change, so does the water, and the warmer cooling water results in less energy efficiency. However, we do not include the minor changes in additional fuel use that would occur due to higher-temperature cooling water—under the assumption that autonomous energy-efficient improvements over the next 40 years will limit the increased demand for fossil fuels.

Temperature-Sensitive Energy Use: We do not include increased energy use resulting from increased temperature for the same reasons noted above. Assumed autonomous technology improvements in the macroeconomic referent (i.e., the base case of the REMI model without climate change) improve energy efficiency over time. Within the REMI model, future increases in energy prices cause price-induced changes in efficiency based on historical estimates of response characteristics, that is, how people have behaved in the past to similar increases. Future (unmodeled) increases in the price of energy—possibly caused by increased demand for energy due to climate change—would feed back on the economy to again reduce demand. Commercial substitution of heating with cooling for climate change may balance out, and residential demands are more sensitive to price changes (Wilbanks et al. 2008). The inclusion of temperature-sensitive correction could consequentially be counting twice for impacts already implicitly included elsewhere in the analysis, and they are therefore neglected.

Additionally, we have defined identical values for the increased temperature across all the simulations, i.e., at the various exceedance probabilities, by specifying a motif (see Section 3.1.3). That is, the temperature itself, and therefore, the impact of temperature is the same across all simulations. We are not concerned with how mitigation could affect the uncertainty in temperature levels. We start with the A1B scenario across the multiple climate models and use the runs of these models as an ensemble, as is.

Sea-Level Rise: Because the analysis does not go beyond 2050, the impacts of rising sea levels are neglected (Sokolov et al. 2009). A review of coastal-facility and topological data indicate that the existing precautions are adequate to accommodate sea-level rise and routine storm surge through 2050. In this context, we also do not consider increases in the frequency of hurricane events historically experienced, on average.

Salt Water Intrusion: We do not include salt water intrusion, the movement of salt water into a non–salt-water environment, because the excess use of ground (and surface) water in the hydrological referent (see Section 3.2.4) contributes much more salt water intrusion than the minimal sea-level rise prior to the year 2050. Simply put, the hydrological referent indicates that the supply and demand is already out of balance, pre-2010.

Intra-Annum Dynamics: We focus our analysis on the lower-precipitation end of the precipitation probability distribution. As our focus is on the reduction in precipitation, we exclude the added costs from flooding. Even though our analysis incrementally simulates into the future only on an annual basis, we do recognize the change in intra-annum precipitation, i.e., seasonal precipitation variation within a year. A likely response to any change in precipitation is to build more low-cost earthen dams for storing water to level the imbalances in supply and demand over the year. The costs associated with this type of solution are not significant compared with the other costs included in this analysis. Note that these same planning procedures based on dams could be used to limit the impacts of flooding to some extent. Other sections of this report provide expanded discussion of considerations for intra-annum impacts, e.g., the Pacific Northwest snow-pack discussion in Section 4.4.

Evapotranspiration: Hydrologists talk of evapotranspiration as the transfer of water from the earth into the atmosphere by evaporation from surface water and land and by transpiration from vegetation. While studies indicate that climate change affects the rate of evapotranspiration, the impact is minor compared with the precipitation changes among the simulations in this analysis. Increased evaporation would further reduce the supply of water and hence the availability of water. Therefore, we hold the ratio of runoff water to total precipitation at its historical (constant) values in the analysis. By definition, this means that we are also holding the ratio of evapotranspiration and ground-water recharging to total precipitation at its historical (constant) value for each state and county. If there actually is increased evaporation as a result of climate change, the impacts noted in this study have been underestimated. Lastly, because we are not separately running the actual AOGCMs as part of this analysis, the climatic calculations to correct for changing evapotranspiration are beyond the scope of our analysis.

Cost of Water: If we compare the cost of obtaining water by purchasing water rights and note that the water should be priced at a comparable rate of cost to that of providing additional storage for the water, such as by building earthen dams, our calculations indicate that the cost of the purchase of such rights is small compared with the cost of physically accommodating reduced water availability. We show the cost of purchasing rights is relatively modest in Section 3.2.3. Applying the cost of both flood protection and additional water storage could constitute double counting, as the same dam could be used for both purposes. Our approach avoids this potential double counting.

Ecological Loss: We do not attempt to capture the value of ecological losses, nor have we considered pest and disease levels in agriculture or the ecosystem beyond those implied under historical (normal) temperature and precipitation conditions. The historical data include such ecological losses.

Human Health: We also purposely do not address the cost of potentially increased levels of human diseases resulting from climate change. Our purpose is to compare our macroeconomic referent (the base-case REMI forecast) across impacts associated with climate-change uncertainty. On one hand, it appears that the analysis of disease impacts is not yet sophisticated enough to quantify even an initial level of confidence in the estimates of changing disease conditions. Patz (2002) attempted to quantify the impacts of diseases, but the dominant disease risk in the United States is associated with flooding. On the other hand, health policy is currently a part of the national agenda and makes the consideration of a no-climate-change basis for future U.S. health conditions unquantifiable.

We do not consider the health impacts of increased pollution levels associated with climate change. These impacts appear to be associated with temperature levels (Tol 2000a). Although temperature and its variation is a component of this analysis, the emphasis of our uncertainty analysis is on reduced precipitation. Further, it is unclear whether minimal adaptation efforts (i.e., minimal costs) could reduce these impacts.

Moreover, for the United States, there appear to be both positive and negative estimates of health impacts due to climate change (Tol 2002b; Kunkel 1999). For example, warmer temperatures may significantly reduce cardiovascular-related deaths, and much drier conditions may reduce the spread of disease (Tol 2002a; Bosello et al. 2006). However, wetter conditions in more northern latitudes may increase infectious diseases (Shuman 2010). The net risk-adjusted impact of climate change on health care may balance out the positive and negative risks and result in an expected net value that has close to no impact.

Nonetheless, even in the absence of explicitly estimating health impacts, the analysis here shows significant impacts on the health care system. These impacts are primarily negative as a result of lost employment and lost income that restrict the use of discretionary health care. Because this analysis addresses the impacts of climate change in the absence of any policy interventions, we do not assume the U.S. government will intervene to fund this loss of health care. Whether the government transfers the loss to itself or leaves it as a responsibility of individuals in the population, the result is still a financial loss and is so recognized in this analysis.

Tourism: We do not consider tourism in the analysis so that we can focus on the core interindustry and migration dynamics within the economy.

Insurance Costs: We explicitly omit insurance costs, but these costs are implicitly treated in the analysis. In principle, the analysis determines the costs of such losses. An insurance company mainly acts as a funds-transfer agent. Presumably such an agent receives the funds from an industry that pays for the intra-industry damage. As a simple example, each of us (as a modeled residential sector) pays homeowner's insurance to cover losses to our own personal property, but these insurance costs do not cover the losses to a building downtown owned by someone else. When a homeowner pays insurance and then recovers losses from the insurance company, the net cost to the aggregate residential sector balances out except for the intermediate processing costs of the insurance company. Tracking such intermediate cash flows from some industry to its associated insurance company and then back again to the industry would not affect the net results and would have introduced unnecessary complications in the analysis.

Rest of the World: Given the limitation that this is a CONUS-centric analysis, we assume that the rest of the world can and will accommodate U.S. import needs (especially food). We then do calculate international trade considerations along with additional considerations and details that other researchers have suggested are important (Tol 2002b; Niemi 2009a, 2009b). Although climate change may improve the agricultural and principal industries of Canada, Russia, and elsewhere, the combined impact of the changing global trade and climate change on other countries is relatively unstudied. A recent study, however, notes that global agricultural prices will rise with climate change (Nelson et al. 2009). The adaptation in less-developed countries (who are predicted to experience the brunt of the physical impacts of climate change) would require funds that are largely affected by their export (U.S. import) revenues. Assuredly, global markets will change in the future with an assumption that costs will rise, but these uncertain conditions do not change the policy perspective engendered by our study.

Internal Migration: Over the 40-year period, the cost of living in certain areas increases in comparison with other areas where the costs of adapting to climate change are less. Areas with less precipitation will likely experience increases in the costs of goods and services to a larger degree than those with more precipitation. Companies expand or contract, as the demand for their products and services changes. When business opportunities contract, a portion of labor (the population) migrates as its employment options change. Unlike most other studies of climate change of which we are aware, our analysis includes these dynamics of internal migration. We use the total population of the United States as forecasted in the macroeconomic referent (see Appendix D). We do not consider changing birth and death rates from changing climatic conditions, though the rates do change over time as forecasted in the macroeconomic referent. The changes observed in state populations across exceedance-probability simulations are entirely due to internal migration.

International Migration: Because issues related to international immigration are in the realm of public policy, we do not assume there is any additional immigration or emigration beyond that forecasted in the macroeconomic referent.

Dam Operations: Our study probably underestimates the impacts of water availability from increased precipitation that occurs out of phase with the snow-based storage design of the Pacific Northwest dam system. Other analyses seem to indicate that reduced water levels do not appear to reduce river-transport capabilities but do have an impact on hydroelectric power (Miles et al. 2000; Niemi 2009a, 2009b; Bull et al. 2007; NRC 2008) that is not captured in our analysis. Thus, the reported absence of negative impacts from climate change within the Pacific Northwest in our study is more the result of simplification of the analysis than from the lack of these impacts. Such impacts are noted in University of Washington studies (Niemi 2009a, 2009b) and in the study by Karl et al. (2009). Some studies argue that changing how the dams are operated, albeit with other ecological impacts, could maintain either electric generation or other water needs (Payne et al. 2004). Estimates of the added costs of electricity for the Pacific Northwest, based on assumptions of operational inflexibility, are presented in the University of Washington study (Niemi 2009a, 2009b).

Inventory and Investment Timing: We assume that the investment to adapt production with reduced water occurs within the year that reduced water availability is recognized. This time frame further implies that adequate inventories are available to sustain demand during presumed short-term reduced production and that the production is made up over the remaining part of the year. The alternative would be to presume temporary product shortages with ensuing indeterminate analyses of how much prices would vary as a result of hoarding and the existence of exaggerated construction and commodity cycles. We do not have the ability to address these latter considerations.

Investments: Once an investment has been made to reduce water needs, only further reduction in availability would cause more investments. The production costs that are a consequence of the investments are additions to the future price and thus affect the future demand for the sector's output in the particular state. Reduced output resulting from reduced demand would cause unemployment and population migration. Note that national accounting conventions (for example, the United Nations System of National Accounts or the U.S. National Income and Product Accounts) credit adaptation investments as an *addition* to the GDP.

Alaska and Hawaii: Physical climatic impacts are only applied to the contiguous continental states. Alaska and Hawaii are not directly affected. These states, however, would receive benefits from added demand and immigration from the directly affected states. These positive impacts are minor, although possibly understated, and are contained in the reported numbers at the national level.

Correlation Between National And State Precipitation Uncertainty: The data set we use is not complete enough for us simultaneously to consider national precipitation uncertainty and state-level precipitation uncertainty. Even though each state has its unique motif and its normal precipitation levels, we apply the same proportional change in national precipitation for any exceedance probability to all the states. An analysis that fully characterized the uncertainty in both the national and state-level precipitation would increase the overall uncertainty, and thereby increase the potential for low-probability, high-consequence conditions. Consequently, the most likely outcome of a more statistically sophisticated analysis (if data were available to do so) would be an increase in the summary risk.

Analysis Balance: The use of the fixed pattern of water and temperature volatility (the motif) probably overestimates the damage cost at the high exceedance probabilities where the volatility of precipitation may be more benign. Conversely, because the analysis excludes (1) flooding costs that could be larger than noted in the existing studies, (2) disregards potentially high levels of precipitation implied at the upper confidence extremes and (3) neglects costs from infrastructure-damaging extreme wind and hot weather, the analysis probably overestimates the damage costs at the high exceedance probabilities. However, the fixed motif does not capture worsening extreme weather at the lower exceedance probabilities that could physically damage facilities. The net effect appears to be a potential underestimation of the costs resulting from extreme (low-exceedance-probability) climate-induced weather that destroys productive capacity.

2.7 Historical and Future Continuity

The year 2009 is history. Although the AOGCM climate-change analyses include impacts from 2000, those changes from 2000 to 2009 (inclusive of both years) are already implicitly incorporated in the modeled and real-world economy. The models that simulate the economy use the recent (weather-responsive) historical data in their construction and calibration. The consequences of GHG emissions through 2009 will have impacts that may last millennia (Solomon et al. 2009) and are an enduring component of present and future economic evolution. Therefore, from a modeling perspective, the 2000–2009 consequences of climate change have no additional impact on any hydrological and macroeconomic models. All future climate change must be compared with the average 2000–2009 values that have already been incorporated as the new "normal" climate conditions implicit within any macroeconomic referent.

Macroeconomic models do not explicitly consider climate-change phenomena. Yet in their base-case forecasts, they implicitly assume unchanging weather for every future year. In this study, we then only determine the additional climate-induced risks that occur from 2010 to 2050. We use the average of the climate-ensemble from 2000 to 2009 to represent the "normal" weather that underlies the projection by the macroeconomic referent in the absence of added climate change. We ramp in the specified conditions of each sampled exceedance probability over a five-year transition period that starts from the (ensemble-average) 2009 historical values.

In this study, we use the IPCC climate-model ensemble as the macroeconomic-referent statement of the climatic future. In many versions of system dynamics and econometric (statistically estimated) modeling, the models reproduce history and continue into the future as a part of the analysis and validation (Meadows et al. 1974; REMI 2007). The macroeconomic, hydrological, and climate referents must all be self-consistent. The average conditions in the climate-model ensemble between 2000 and 2009 are normalized to ensure these climatic conditions do not generate any impacts on the macroeconomic model over history. The future variations in weather from the climate-model projections are what define the climate-impact simulations between 2010 and 2050. Similarly, the output of the hydrological model is normalized to generate no (new) shortages over the 2000–2009 historical period. Implicitly, if there were historical shortages, these impacts are already implicitly "corrected for" in the macroeconomic model (i.e., the REMI model). The Sandia hydrological model determines the differences in physical water-supply conditions, based on the results of the climate models, compared with the water-demand conditions implied by the macroeconomic referent. This maintenance of self-consistency across the chain of models for the purpose of determining comparative impacts acts as the primary foundation of the analysis.

3 Climate Uncertainty and Impact Quantification

If we are to quantify the risk associated with climate change on the well-being of the U.S. economy, we need to understand the uncertainty associated with climate change and how to propagate the physical impacts of this uncertainty through the economy. Because the emphasis in our study is solely on the policy relevance of climatic uncertainty, we define the macroeconomic model, as we do the hydrological model that connects the climatic information to the macroeconomic simulation, as deterministic. In other words, all the uncertainty in this study comes from the climate-change forecasts that we use as input to this analysis. We neglect all the uncertainty in the hydrological and macroeconomic models. This approach of isolating the impact of climate uncertainty from the calculations in the hydrological model and the macroeconomic model avoids the complications of compounding the uncertainty over the multiple component models used in the assessment (Dessai and Hulme 2004).

Section 3.1 communicates the basic features of climate-change uncertainty and how we characterize them for use in the risk assessment. Section 3.2 explains how we determine the hydrological impacts. Section 3.3 discusses how we use the REMI model to determine the macroeconomic impacts of climate change.

3.1 Characterizing Climate Change

For the globe, Figure 3-1 shows the mean percentage change in precipitation due to climate change in the 2080 to 2099 time frame compared with recent historical values for 15 AOGCMs (atmospheric and ocean global-circulation models) in the climate ensemble under the SRES A1B scenario (IPCC). The stipple marks show where 80% of the models agree on the sign (positive or negative) of the change. Precipitation in North America varies by geographical region and by the specific AOGCM, with the annual mean precipitation of this ensemble projected to decrease in the Southwest but increase in much of the remaining areas (Bates et al. 2008). Individual studies project both increases in extreme precipitation and droughts (Meehl 2000; Trenberth 2008). The AOGCMs in general, project larger changes in precipitation extremes, such as intense downpours, than in mean precipitation, which is the annual average rainfall (Field et al. 2007; Kundzewicz et al. 2007).

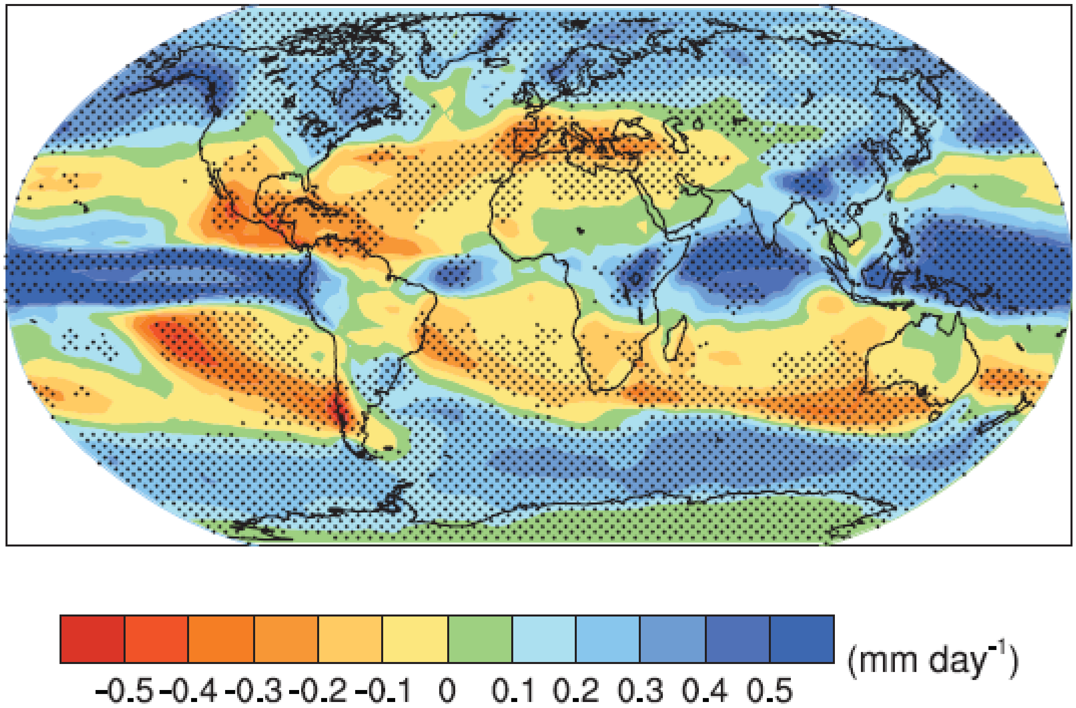

Figure 3-1. Precipitation change. Source: Bates et al. (2008).

Figure 3-2 shows the corresponding temperature changes from the 2080 to 2099 time frame compared with the historical values for the 15-model ensemble. Temperatures increase across the entire CONUS (continental United States), with growing magnitude from the Southwest to the Northeast.

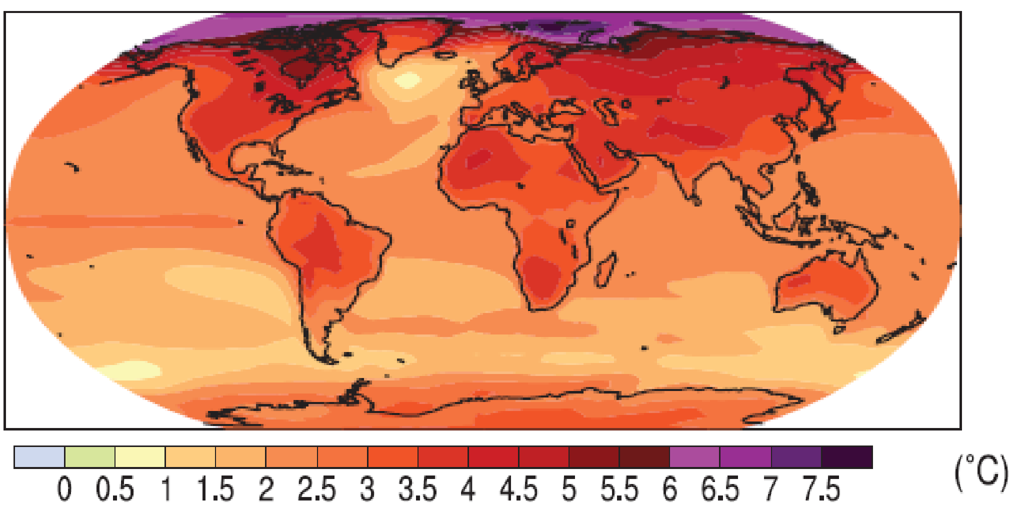

Figure 3-2. Temperature change. Source: Bates et al. (2008).

By and large, the mean of the 15-model ensemble shows increased drying over CONUS, as indicated by the colors associated with the negative percentage values (yellow to shades of orange and red) in Figure 3-3. Individual models may indicate that there are increases in precipitation in some states, while other models indicate that there are decreases in those same states.

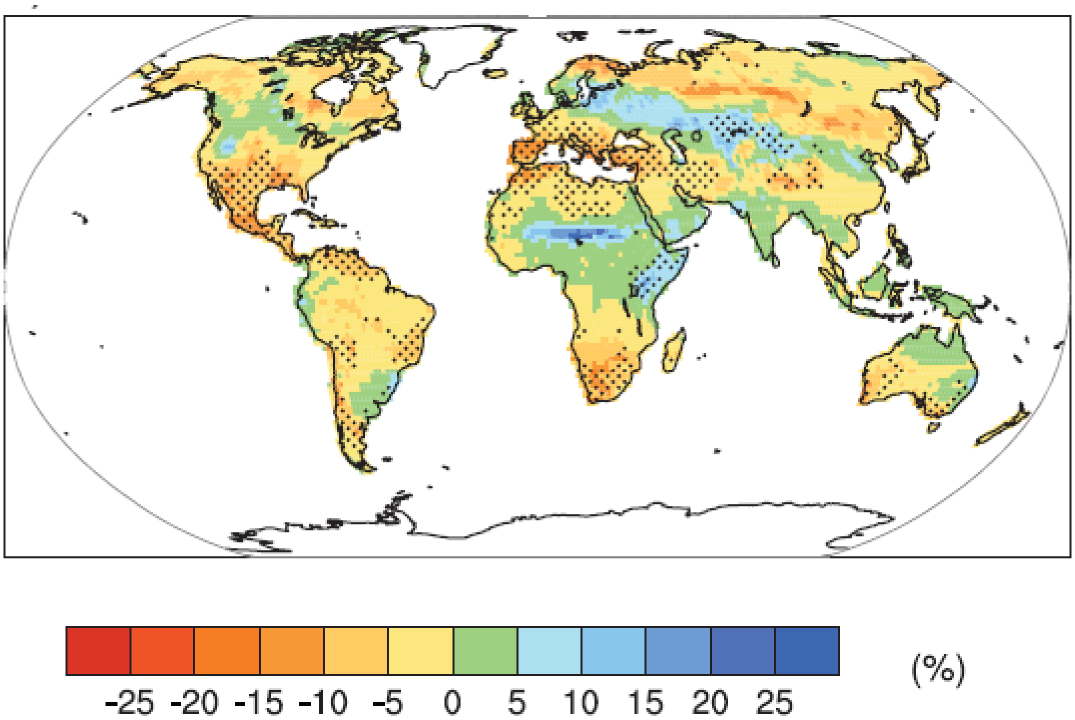

Figure 3-3. Soil moisture change. Source: (Bates et al. (2008).

In the risk assessment, we analyze the consequence of changes in precipitation implied by the ensemble results at the national level over the entire range of exceedance probabilities, from strongly increased precipitation (100%) to strongly decreased precipitation (0%). However, because of limited data in the climate ensemble, we cannot independently calculate how the individual states would vary in precipitation as the nation is varying. Similarly, there is inadequate information to self-consistently vary the pattern of frequency and intensity for temperature and precipitation over the simulations (Tebaldi and Sanso 2009). To address this issue, we use a motif that relates national precipitation to the volatility present in state-level modeled temperature and precipitation. The motif is a representative pattern that corresponds to the 10% exceedance probability and is also consistent with the overall trends shown in Figure 3-1 through Figure 3-3. We selected the 10% exceedance probability because our concern is centered on the risk associated with the tail of the precipitation distribution. The total risk is sensitive to the consequences at low exceedance probabilities. Therefore, the selected motif should be most representative of the climatic conditions associated with the tail region of the probability distribution, as communicated in Section 2.3. Using a motif from a climate-model run that represented a higher exceedance probability would underestimate the impacts for low exceedance probabilities. On the other hand, the use of the motif from a climate-model run that represents a low exceedance probability appears to only marginally overestimate the calculated risk in central U.S. states that show minimal climate risk in all the simulations.

The results we use as the motif were produced by the medium-resolution MIROC3.2 climate model from the PCMDI data set. The MIROC3.2 results fit within the mainstream envelope of climate (precipitation) forecasts from other models (Jun et al. 2008; Milly et al. 2005), and the precipitation pattern within this MIROC3.2 model matches the 10% criterion. Note that there is both a high-resolution and a medium-resolution version of the MIROC3.2 model. All subsequent mention of MIROC3.2 denotes the "medium res" version of the model. Effectively, the MIROC3.2 model simulation serves as the basis for all the motifs (generically called the motif) used in this study. The motif acts as a pragmatic, nonetheless necessarily imperfect, referent that forms the foundation for climate-policy discussions. Section 3.1.3 explains how the motif is quantified.

Other studies have also had to revert to selecting a motif to make the uncertainty analysis manageable (Hallegatte et al. 2007). Any AOGCM run produces a specific coupling of precipitation and temperature conditions. It would violate the self-consistency of the run to treat precipitation and temperature as independent entities separately affected by model uncertainty. Through the use of the motif, each simulation maintains a self-consistent, fixed relationship between precipitation and temperature and their associated frequency and intensity. By using the motif, we attempt to minimize the statistical concerns (or at least make them transparent) when sampling a single variable (precipitation) to reflect variability across multiple dimensions (Hall et al. 2007). Thereby, the fixed motif also simplifies the conceptual approach for propagating the uncertainty within simulation models.

Although the motif is not dramatically different from other patterns produced by other models, the motif does capture the impact of climate-change volatility that is consistent with, and representative of, the temperature levels correlated with the precipitation. The chosen motif contains a realizable sequence of how precipitation levels may vary over time in a given U.S. state compared with other states. Over the 100% to 0% exceedance-probability range of precipitation probability, the simulations of any U.S. state include both increased and decreased precipitation. As stated above, the IPCC data set is not extensive enough to allow the joint determination of a primary uncertainty (such as precipitation or temperature) and their associated frequency and intensity variation among state-level regions. The variability reflected in the motif produces only secondary impacts (see Section 4.3). The use of more-sophisticated statistical methods would not appear to significantly affect the results of this study. The impacts from the volatility contained in the motif are additive to those impacts caused by the variation in long-term precipitation that is used in this study as the primary uncertainty. The motif includes the downward trend in average precipitation correlated with an increase in average temperature that is the fingerprint of climate change within the midlatitudes (Portmann et al. 2009).

While it is true that the use of another motif may have changed our simulated relative precipitation increase or decrease at the state level, an analysis that fully characterized the uncertainty in these features would increase the overall uncertainty, and thereby increase the potential for low-probability, high-consequence conditions, even while it improved the detailed precision of the hydrological referent. The purpose of this study is to illustrate a process for generating the risk profile among the states through the use of a macroeconomic referent impacted by the climatic uncertainty. This study does not attempt to comprehensively discriminate among the different components of climate-change uncertainty. When and if climate analyses and methods allow it, the process used in this study can accommodate fully quantified uncertainty in the motif. Given the urgency in developing a U.S. response to human-induced climate change, we believe it is preferable to use the currently incomplete state of knowledge rather than wait for future climate research to supply a more precise picture.

3.1.1 Characterizing Climate Change Uncertainty

Current data indicate that the present trajectory for CO_2 emissions exceeds even the SRES A1F scenario (Steffen 2009). Despite this fact, we use the A1B scenario because we assume that technology and future economic growth will maintain a trajectory that is more consistent with the less-severe A1B scenario.

We use the ensemble of the 53 PCMDI A1B runs as an appropriate (useful and relevant) basis for quantifying the climate uncertainty used in our study. The actual (or real-world) uncertainty is probably much larger than the uncertainty characterized by the ensemble (Jun et al. 2008; Knutti et al. 2008), and therefore the estimated summary risk (integral of probability-weighted consequences) underestimates the true risk value. The ensemble results are publicly available for review and use from Lawrence Livermore Laboratory via the Internet (http://www-pcmdi.llnl.gov/). These results come from the IPCC-authorized work on climate change. These IPCC analyses are the most visible and widely used source of information on the potential outcomes of climate change.

The PCMDI data sets contain information that goes from every three-hour averages to every-month averages, with coverage over the 2010–2050 years of concern in this study. For other than agricultural impacts, we aggregate these data into annual values. We choose to use only the annual uncertainty in precipitation for several reasons. First, the precipitation estimates among the climate models for June-July-August and December-January-February can vary even in sign (positive or negative), but the annual values are much more consistent (Allen and Ingram 2002; Seager et al. 2008; Zhang et al. 2009). Second, the volatility of precipitation is more important to agricultural production than is the actual level of precipitation. The measures of volatility across the models do appear to be consistent (see Section 3.2.1). Third, economic activities can generally accommodate or are relatively immune to differences between seasons. Fourth, the uncertainty in the sign of impact among the climate models and the large amount of volatility and biases (compared with historical values) at the short time-constants (hours and months) largely disappears at the annual level (Sheffield and Wood 2008). Because this intraseasonal aspect of uncertainty and volatility has minimal bearing on the analysis herein, the validity of the risk assessment actually improves because the specification of uncertainty improves.

The PCMDI data do not contain an exhaustive uncertainty analysis for any of the individual AOGCM models. If the data set contained a more complete sensitivity analysis of all the individual models, the uncertainty within the ensemble would likely be even larger, and the results of the risk analysis would therefore show larger costs. Studies note that the variation among different AOGCMs is much greater than the variation found solely within individual models (Giorgi and Francisco 2000; Knutti 2008; Murphy et al. 2004). We adopt this observation regarding variation as a general assumption. Thus, the existing PCMDI data not only have the obvious value of actually existing, but the data also contain a recognized level of uncertainty.

In other words, we use the PCMDI ensemble results from the 53 runs of the SRES A1B scenario as our representation of climate uncertainty not because these results are "right," but because they act as an acceptable basis for making risk-informed decisions and are used to support that goal (Vicuna et al. 2009). Our emphasis is neither on risk-informed policy nor on a risk assessment of alternative initiatives. Using the term "risk-based" in that context often implies a sense of knowledge that has clearly not yet been achieved for climate science. In future decades, climate science may have the level of valid knowledge and sufficient accuracy that is required for risk-minimized policy making (Knutti 2008), but climate policies need to be made long before the climate community comes to common agreement on quantifying the uncertainty in future climate conditions.

We accept the PCMDI model results as-is. That is, we do not question or analyze the validity of these results in this study, nor do we even recognize error biases in their forecasts. Others have noted that the random selection and use of the models do not result in significantly different conclusions (Pierce et al. 2009). In other words, had we selected, say, runs from fewer than the 24 models, the conclusions would likely have been similar for the smaller collection. The differences among the model results tend to balance out when they are examined as a group. We are interested in the ensemble results as a rational and useful representation of climate uncertainty. By using 53 runs from 24 models, we take advantage of the information within the ensemble and recognize that there is no consistent manner to correct for perceived error biases (Tebaldi and Knutti 2007; Jun et al. 2008). Other researchers note that the relative uncertainty provides the policy-relevant information and is well supported across different studies (Knutti et al. 2008). We primarily focus on the variability in precipitation among the runs in the ensemble, but do, as discussed below, also use the runs for selecting a referent, the motif, of future weather intensity and frequency. Some researchers note that an ensemble still underestimates the full uncertainty of future climate but that the information has value for guiding decision makers (Stainforth et al. 2007a; Räisänen and Palmer 2001; Allen and Ingram 2002). That larger uncertainty would imply a greater risk (Stainforth et al. 2007b) than the estimates in our study. Other researchers, however, indicate that the accuracy of climate modeling is improving to the point where the uncertainty is converging (Reichler and Kim 2008). That is, the uncertainty is becoming adequately defined for use in analyses that quantify the impact of that uncertainty on the risk from climate change.

Some modelers use statistical downscaling methods to gain more insight about climatic conditions in specific locales within a geographic area, like a county, when the information they have is at a lower, less-detailed level of resolution, such as that of a state or region. Downscaling is an approach that attempts to extend the resolution for the IPCC runs to a local scale that is consistent with historical statistical characterization, i.e., the relationship between the state averages and county-level specifics on precipitation-related variables. We do not apply downscaling methods on the PCMDI runs to generate county-level values for three reasons. First, the use of downscaling could turn a broad policy discussion about the impacts of climate change into an abstruse science debate that focuses on the particular downscaling method employed. Second, the added skill, that is, accuracy, that downscaling provides for improved forecasting remains an open question (Dibike and Coulibably 2005; Santoso et al. 2008). Downscaling is highly dependent on the particular AOGCM used, and it is not clear whether it produces additional information (Alkhaled et al. 2007; Collins 2007). And third, a national policy discussion that depends on detailed local phenomena contradicts the purpose of using models for informing national policy discussions. To meet the needs of policy makers, we believe that the state level is the appropriate level of aggregation for this analysis. To inform policy discussion, our analysis exclusively addresses state-level impacts. Even if higher resolution data supported consideration of detailed, heterogeneous local features, it would be necessary to again aggregate the information to the state level for our purposes.

Figure 3-4 shows the annual variation in national-level precipitation across the 53 runs of the A1B scenario over the years 2010 to 2050. The points are calculated by summing the precipitation reported in each ensemble-model run over the complete and partial grids that contain the area representing the United States. Each colored line represents the results of a different computer run.

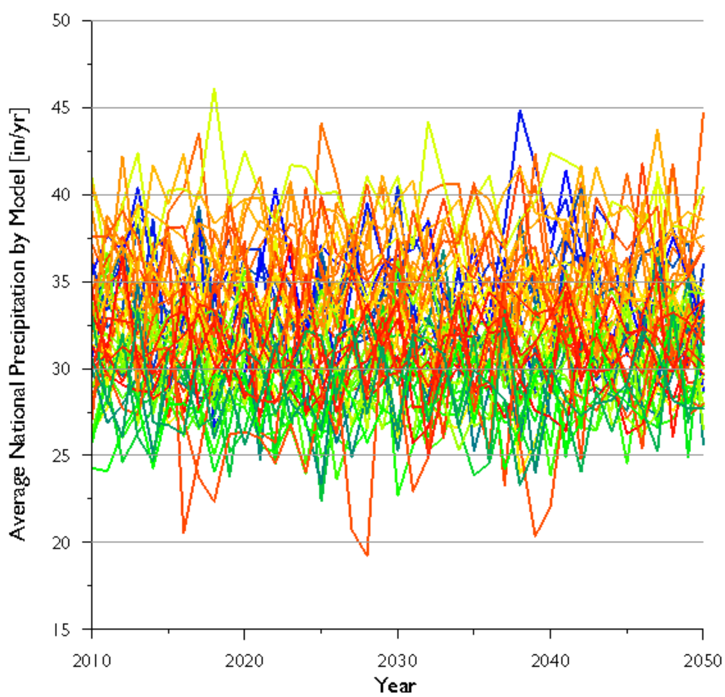

Figure 3-4. National precipitation from each of the ensemble models.

Figure 3-4 gives a clear picture of the uncertainty, hence volatility, in the 53-run ensemble. The range across most of the runs appears to be between 27 inches and 37 inches per year, with a few runs several inches below and above that range and a small number spiking dramatically in both directions. One of the most visible runs is the dark blue line. Similar to the others, the blue line has a lot of volatility, with high and low swings within relatively short time spans. Notice that in the very same years that some runs show high averages, other runs report low averages. But on the whole, the runs in some sense appear to balance out in a range that likely goes from about 30 to 35 inches over the time period.

The climate models produce data that have both spatial attributes (different values at different geographical places) and temporal attributes (different values at different times). All the models represent the globe as a sphere covered by a grid pattern of areas with climatic conditions in each area changing over time. To aggregate the detailed data from the ensemble runs to state-level values over a specified year, we use a weighting process. If f is the fraction of the model gridding that is contained in an area (such as a state or the nation) and V is the value of any quantity estimated for that grid (such as precipitation or temperature at a specified time), then the average value $\bar{V}_{A,T}$ (such as the national precipitation in Figure 3-4) is the sum over the gridding, g, and the modeled time instantiations, t, to the area, A, and the time resolution, T, of interest:

$$\bar{V}_{A,T} = \sum_{t} \sum_{g} f_{t,g,A} \times V_{t,g} \,. \tag{3-1}$$

Because of our interest in economic impacts, using economic-value or population weighting may seem more appropriate than area weighting for aggregating the data to the national level when developing the probability distribution. However, any approach that uses anything other than the area-centric logic inherent in the actual AOGCM runs generates distortions and inconsistencies in the statistical meaning of variables as the data flow from the hydrological component of the simulation through the socioeconomic, i.e., REMI model, component of the simulation.

As discussed in Section 2, a gamma distribution is commonly used to represent the probability distribution function for precipitation (Groisman et al. 1999; Watterson and Dix 2003). Figure 3-5 shows the projected cumulative probability of precipitation in inches per month for New Mexico and New York over the years 2010 through 2050, as generated by the MIROC3.2 and CCSM3 models, respectively.[2] (See Randall et al. [2007] and Meehl et al. [2007b] for a discussion of the IPCC climate models.) We choose these states to illustrate contrasts, with New Mexico being a dry southwestern lowly populated area and New York representing a wet northeastern highly populated area. The selection of New Mexico also serves as a representative example to understand the results of our work, given that members of the study team are knowledgeable about the economy and the water issues in this state.

[2] The statistical fitting of the PCMDI data to the gamma distribution was completed using MATLAB.

The two graphs in Figure 3-5 show the calculated monthly precipitation of the two models for the areas representing the states of New Mexico and New York as a function of exceedance probability. The models are mapped using whole and partial grids to cover the area of the states according to Equation (3-1). The value, in this example, precipitation, in each modeled grid is taken as homogenous across the grid. The shown state-values are the area-weighted sum for each month, ordered by the magnitude of the values, and then portrayed as a cumulative probability distribution. Visually, the models' results conform to expectation of a gamma distribution and have inconsequential estimated second-order uncertainty, as represented by the dashed lines around the best-estimate solid line. The actual data and best estimate closely approximate each other.

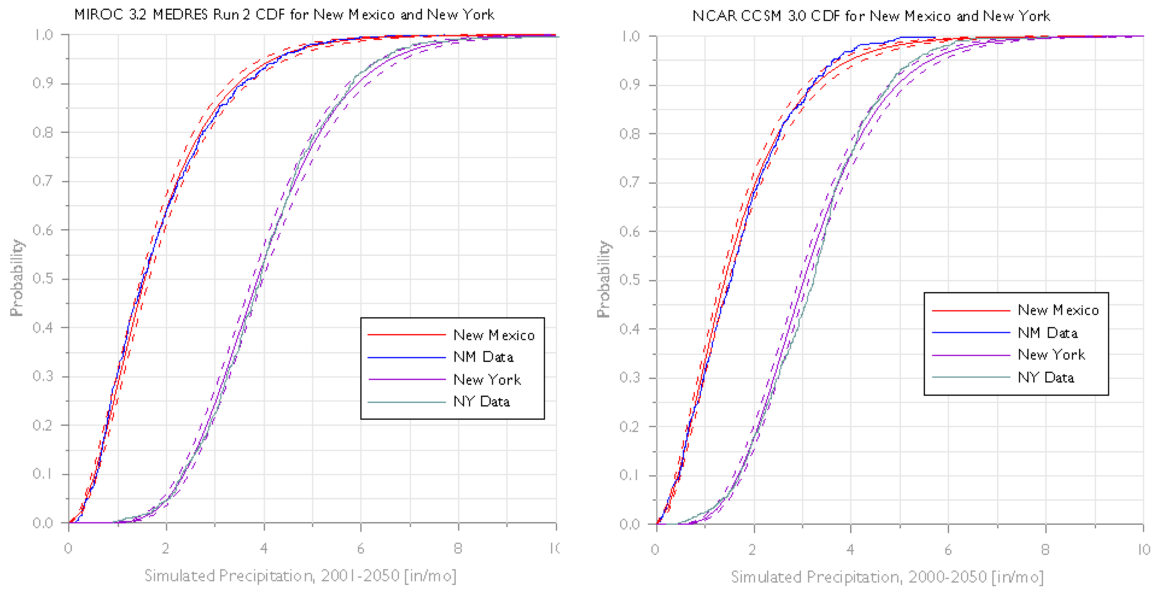

Figure 3-5. New Mexico and New York projected precipitation distribution (inches per month).

The values noted in Figure 3-5 and subsequent graphs and tables quantifying precipitation are consistent with but different from the values indicated historically by the National Oceanic and Atmospheric Administration (NOAA).[3] This discrepancy is an artifact of the weighting process used in Equation (3-1) versus that used by NOAA. The areas within the grids of the climate model each contain a set of results, such as precipitation and temperature. These results represent the average value for those conditions over the entire area denoted by the grid. This sameness of conditions over the whole area is called homogeneity. We map a fractional piece of these areas to produce areas representing states. Grid-based areas that represent mostly a "drier" Texas could partially map to a "wetter" Louisiana. Part of an ocean-dominated area could partially map to a piece of coastal land. Thus, the "mix and match" process of mapping one area to the other can produce distortions. We could use mathematical methods to maintain the exact correspondence to the historical values, but it would be at the expense of no longer exactly reflecting the uncertainty information available with the ensemble of modeled

[3] See http://www.ncdc.noaa.gov/sotc/index.php?report=national&year=2006&month=ann#precip for historical U.S. precipitation or http://www.ncdc.noaa.gov/oa/land.html for all historical data.

estimates. The modeled results reflect a measure of the uncertainty in future climatic conditions. The purpose of this study is to show how the uncertainty in predicted climate change increases the expected risk from climate change and thereby to show the justification for policy to counteract that risk.

Within the analysis, we do not use the actual number calculated for precipitation. Instead, we only compare the model-based calculation of "historical" precipitation to the calculated values at the various exceedance probabilities to determine proportional changes. The historical supply of water used in the hydrological model corresponds to accepted estimates of the actual historical supply (see Appendix A). The historical demand for water derived from the macroeconomic model corresponds to the accepted estimates of actual historical demand (see Appendix A). The estimated historical precipitation is scaled to correspond to that supply, and the modeled precipitation is only used to define proportional changes in the calculated historical supply. Consequently, the absolute value of the estimated precipitation does not affect the analysis results.

Figure 3-6 highlights the same two states in the previous figure; however, the units have been changed to inches per year, and only results for the MIROC3.2 model are given. To obtain these values, we sum the data of Figure 3-5 over the 12 months of each year. Note that the gamma function is still a reasonable representation, as would be expected. The distribution of precipitation as a function of time should be functionally invariant. That is, the distribution should be adequately approximated by a gamma distribution independent of whether the data series is based on daily, monthly, or yearly values. We have observed that the shape of the precipitation distribution does not change, whether we look at different parts of the country, different extremes in the amount of precipitation, or different time intervals, i.e., month and year.

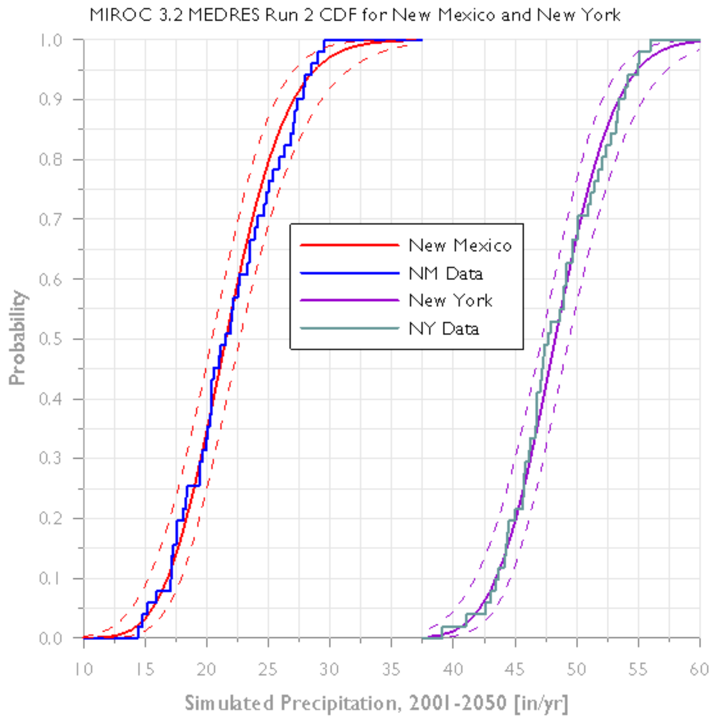

Figure 3-6. New Mexico and New York projected precipitation distribution (inches per year).

Figure 3-7 shows the cumulative distribution of national-level precipitation from all 53 model runs over the 2000 to 2050 time frame.[4] To generate this figure, we calculate the average number of inches per year for each and every ensemble model rather than just for the MIROC3.2 and CCSM3 models used to generate Figure 3-6. We perform this calculation for CONUS rather than just for an individual state, sum over all years to and including 2050, and calculate the annual average. Figure 3-7 is essentially just Figure 3-6 for the entire United States instead of a particular state, and it uses all the model results rather than just one model's results.

[4] Some model data begin in 2001.

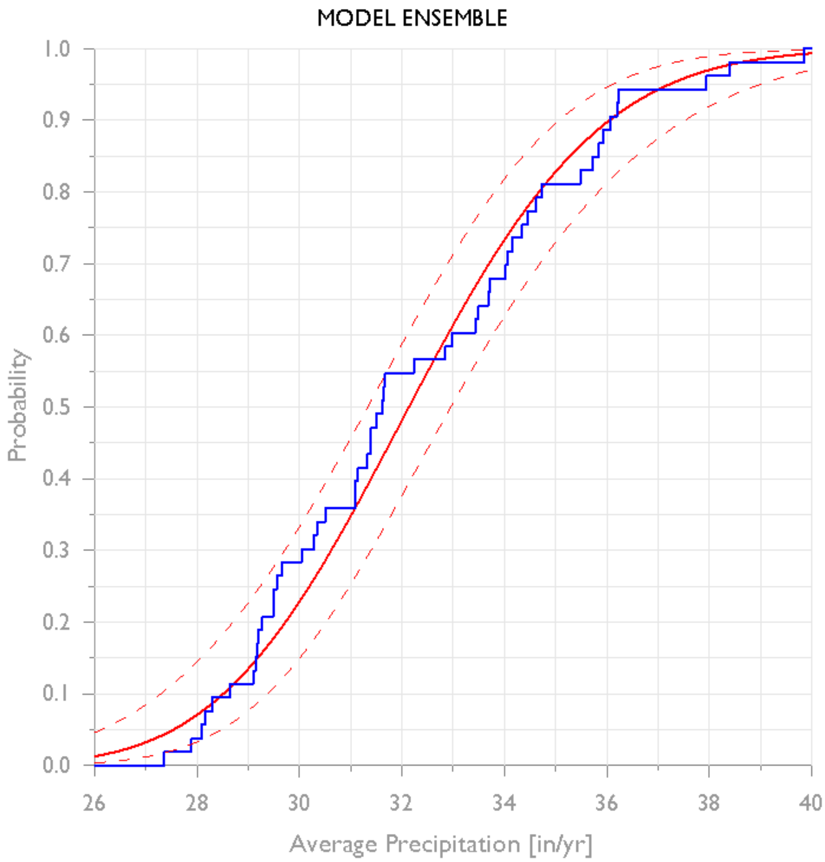

Figure 3-7. National average precipitation cumulative probability.

As an example from Figure 3-7, at the 0.5 (50%) exceedance probability, the median precipitation is close to 32 inches per year for the nation. A much lower probability, say 0.075, shows an average of 28 inches per year. The 95% to 5% confidence interval, which represents the range of the second-order uncertainty, is indicated by the dashed lines. Note the second-order uncertainty is much larger for the ensemble than for the individual models of Figures 3-2 and 3-4. The curve (solid red line) in Figure 3-7 is the primary (first-order) uncertainty in national precipitation that we use to generate the exceedance-probability simulations for the risk assessment. The national level of precipitation at a given exceedance-probability level is available directly from the mean values—solid red line—of the exceedance curve estimated for Figure 3-7. The national level of precipitation at a given exceedance-probability level is mapped to the state level using the state-to-state differences contained within the MIROC3.2 model simulation.

Explained another way, a particular level of forecasted precipitation is associated with a particular AOGCM run. An AOGCM divides the globe into gridded areas. The AOGCM run contains temperature and precipitation detail for each of the gridded areas simulated. We use a model's gridded areas covering the United States and map the areas to the individual states, partitioning and aggregating area-specific data as appropriate. Thus, the national values translate to unique state-level conditions for both precipitation and temperature for use in the subsequent hydrological component of the analysis.

3.1.2 Using Uncertainty for Risk Assessment

As noted above, we use the cumulative distribution of national area-weighted average annual precipitation through the year 2050 as defined in Equation (3-1) to determine the precipitation to use in the exceedance-probability simulations for our risk assessment. For the hydrological analysis, we first map the monthly conditions (for temperature and precipitation) associated with the climate-model grids to the county level to correspond to the detail of the hydrological model in the same manner as it was done for the states. The hydrological model also includes basin-level specificity. The basin considerations account for water flows, which are necessary to know when determinations are made by the hydrological model about where water, which knows no country or state boundaries, goes. We then aggregate the county hydrological results to the state level for input to the state-level macroeconomic analysis.

Note that the state-level aggregation means that the measure of economic activity is now characterized as being homogenous over the state, as is state-level water availability. However, the state-level macroeconomic model also implies homogeneity within the state, and therefore any hydrological data fed to the model must be at the state level for consistency. Nonetheless, the macroeconomic model has also been constructed using county-level resolution. The county-level resolution implicitly captures the historical-average nonhomogeneity of economic activity and therefore the associated local water-availability considerations of where economic activity occurs within the state. For example, economic data for individual cities in New Mexico, including their water supply characteristics, are included in the lower-aggregation process to produce the state-level values. The climate, hydrological, and macroeconomic spatial-data resolution is therefore self-consistent for historical differences within a state. With the state-level motif, the future differences across states change with time as a function of climate change, but the relative intrastate differences remain at their historical relationship. As noted previously in Section 2.6, intrastate considerations are outside the boundary of this study.

We analyze a series of simulations at nine different exceedance probabilities to estimate the distribution of socioeconomic impacts as a function of the changing state-level precipitation. Table 3-1 lists the national exceedance probabilities selected from Figure 3-7 that are mapped to the state level using the state-level motifs discussed above. Associated with each probability are the corresponding national-average precipitation and the ratio (multiplier) between the precipitation value and the 50% exceedance probability. Note that our emphasis is on the lower end of the precipitation distribution tail centered at approximately a 10% exceedance probability, where damage costs begin to rise precipitously.

Table 3-1. Exceedance-Probability Sampling Scheme

Sample %	Precipitation (inches)	Multiplier (50% = 1.0)
1 %	25.777	0.8021
5 %	27.542	0.8571
10 %	28.516	0.8874
20 %	29.726	0.9250
25 %	30.194	0.9396
35 %	31.017	0.9652
50 %	32.135	1.0000
75 %	34.158	1.0629
99 %	39.463	1.2280

The percentage values in Table 3-1 correspond to the 50% probability (solid line) of the cumulative distribution in Figure 3-7. So, for example, the median national precipitation, defined at the 50% exceedance probability in the above table, is 32.135 inches. On average the national precipitation drops by roughly 6 inches (a roughly 25% reduction) when going from a 50% to 1% exceedance probability, but the loss would be different for each state as a result of reduced (or increased) national precipitation because the states each have different levels of average precipitation. At the 99% exceedance probability, the average national precipitation is 39.463 inches, which is 22% above the 50% value. To determine the corresponding state precipitation values at each of the nine exceedance probabilities, we multiply each state's median precipitation value by the multiplier value given in the third column of the table. Each state's median precipitation value, in inches, is the median value of the average precipitation over the 53 PCMDI runs over the 40 years. The use of both the terms "median" and "average" in close proximity is a bit confusing, but it means that at the 50% exceedance probability, there is a 50% chance the precipitation (on average) will be less than (or more than) the precipitation noted, e.g., 32.135 inches, for the nation. The term "average" appears because the data values do represent the average over the 40 years and the 50% exceedance probability is the median of those average values. The annual variation is then captured through the yearly percentage increase or decrease contained in the state-level motifs discussed further in Section 3.1.3. The resulting value, at each of the probabilities, is the available water supply that we subsequently compare to the demand to determine the water availability that the REMI model uses to determine the economic impacts.

The impacts of the simulations are the difference between what the hydrological and macroeconomic models would predict with the historical precipitation sustained into the future and what the models would predict with the precipitation of each exceedance probability used in the future. In the absence of climate change, climatic conditions would still vary in the future. Our climate referent does not contain this variation. The Atlantic Ocean exhibits a cycle of change in sea-surface temperatures called Atlantic Multidecadal Oscillation (AMO). This oscillation changes the precipitation in North America. The El Niño Southern Oscillation (ENSO) is another such phenomena in the Pacific Ocean that changes the precipitation conditions in much of the Western

Hemisphere. El Niño has a relatively short period of oscillation, on the order of five years but highly variable, that would not noticeably change the modeled impacts between 2010 and 2050 compared to assuming a constant "average" value for precipitation.

The highly variable period of oscillation for the AMO is approximately 70 years (Trenberth and Shea 2006). Its variability would not average out over the 2010 to 2050 time frame. Currently, the AMO is in a warming phase that generates additional precipitation. This phase may last until 2035 (Enfield et al. 2001). Further, current climate models do not yet incorporate the AMO with much fidelity (Hurrell et al. 2010; Murphy et al. 2010). The ensemble's historical average, which we use as our historical referent, only minimally reflects the AMO phenomena because each individual model differently captures the AMO and its timing. Combining the results of all the individual climate models tends to cancel the AMO contribution of each model to the ensemble's average. Consequently, it is not possible to develop a statistically meaningful AMO representation for the climate referent that is consistent with use of the simulations for each exceedance probability. Therefore, the referent used to compare the impact across simulations uses a future equal to the calculated historical average. Given the fact that the actual AMO is estimated to produce additional precipitation, as contained in each of the individual model simulations, including MIROC3.2, our process to estimate climate-change impacts could potentially lead to an underestimate of these impacts.

We can estimate the impact of the second-order uncertainty without performing additional simulation analyses by noting that every best estimate for a simulation corresponds to a second-order uncertainty at the 95% and 5% boundaries of the confidence interval according to the values in Table 3-2. The 90% confidence interval (between the 95% and 5% confidence boundaries) capturing the second-order uncertainty is simply the range of possible values that the first-order-uncertainty solid line in Figure 3-7 could have. The solid line is the best estimate of the first-order probability.

Table 3-2. First-Order to Second-Order Probability Map

	First-Order Probability Level		Second-Order Probability Level
Simulation %	Precipitation (inches)	Lower 5%	Upper 95%
1 %	25.777	0.250%	3.918%
5 %	27.542	2.102%	11.429%
10 %	28.516	5.187%	18.412%
20 %	29.726	12.626%	30.193%
25 %	30.194	16.741%	35.591%
35 %	31.017	25.478%	45.889%
50 %	32.135	39.424%	60.576%
75 %	34.158	64.408%	83.259%
99 %	39.463	96.081%	99.750%

Figure 3-8 gives an example of the upper and lower second-order uncertainties for the 50% exceedance probability (first-order uncertainty) listed (and shaded) in Table 3-2. Starting at the 0.5 circle on the red line of Figure 3.8 (which is roughly 32 inches), we follow the vertical line upward to where it crosses the upper (95%) probability curve, which defines the upper second-order probability of 60.576%. This value can be interpreted as there being a 95% chance that the 60.576% exceedance probability for national precipitation will produce less than 32.135 inches of water per year, on average, over the 40-year period. Starting again at the 0.5 circle on the red line, we follow the vertical line downward to where it crosses the lower (5%) probability, which defines the lower second-order uncertainty of 39.424%. This value can be interpreted as there being only a 5% chance that the 39.434% exceedance probability for national precipitation will produce less than 32.135 inches of water per year, on average, over the 40-year period. By drawing curves through the related values, these first- and second-order uncertainties used in the risk assessment are reflected in the summary-risk figure of the executive summary and in Figure 4-2 and Figure 4-3 of Section 4.

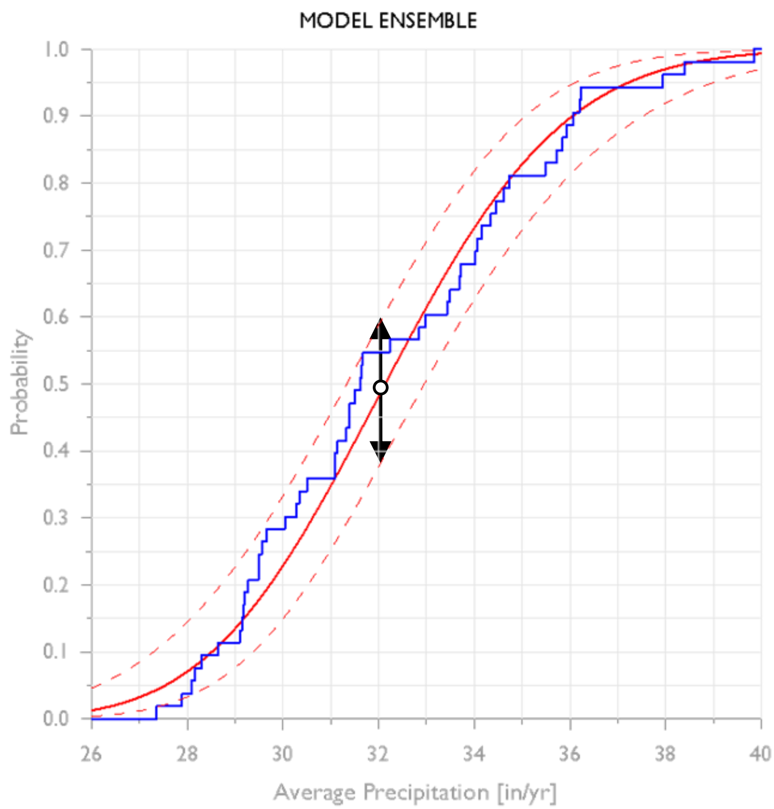

Figure 3-8. Example of determination of second-order uncertainty from 0.5 first-order uncertainty value.

In all cases, each simulation we perform starts with taking the national precipitation at a specific exceedance probability and converting to precipitation at the state level over the 40-year time frame of the simulation. Via the state-specific motif, each of the nine exceedance probabilities we simulate includes the frequency and intensity characteristics associated with drought, flood, and temperature variability.

3.1.3 Motif Specification

The motif acts as the vehicle for comparison across the range of precipitation uncertainty. Using the motif is a pragmatic approach that does not significantly affect the estimation of climate-change impacts (see Section 4.3) and that has a history within climate impact analysis (Hallegatte et al. 2007). Associated with the frequency and intensity of precipitation, the motif also then expresses the relationship of temperature (with volatility) to precipitation. Although more-sophisticated studies could exercise the suite of models to extend this work by including frequency, intensity, and secondary uncertainty, such an effort would be prohibitively time consuming even on the next generation of supercomputers. As pointed out by Tebaldi and Knutti (2007), studies using a single model would not capture the range of both epistemic and aleatory uncertainty captured in the full suite of models.

Figure 3-9 depicts the precipitation component of the national-level motif, though we do not use this motif at the national level in the analysis. We present it here to illustrate what a motif looks like. The national-level motif for precipitation is normalized to have an average value of 1.0 over the 2000–2009 period, with the volatility then measured as a percentage difference from the norm. The motif constitutes a large collection of local information on precipitation and temperature volatility across the nation. Each state has its individual, normalized motif for temperature and precipitation based on the mapping of the MIROC3.2 gridded, time-dependent data to the state area. These submotifs contain the state-level dimension of the entire national motif. State volatilities are larger than the national volatility. The relatively modest 40% swings in national-average precipitation implied in Figure 3-9 are typically larger within the motif view at the state level, reflecting larger swings in drought (and flooding) conditions. To capture agricultural impacts, there are state-level submotifs that contain the monthly variation. The monthly variation, however, is primarily used to calculate the local drought index across years needed for the agricultural model noted in Section 3.2.2 and in Appendix A. The state-level submotifs with annual variations are the primary determinants of water availability for other economic activities within the states.

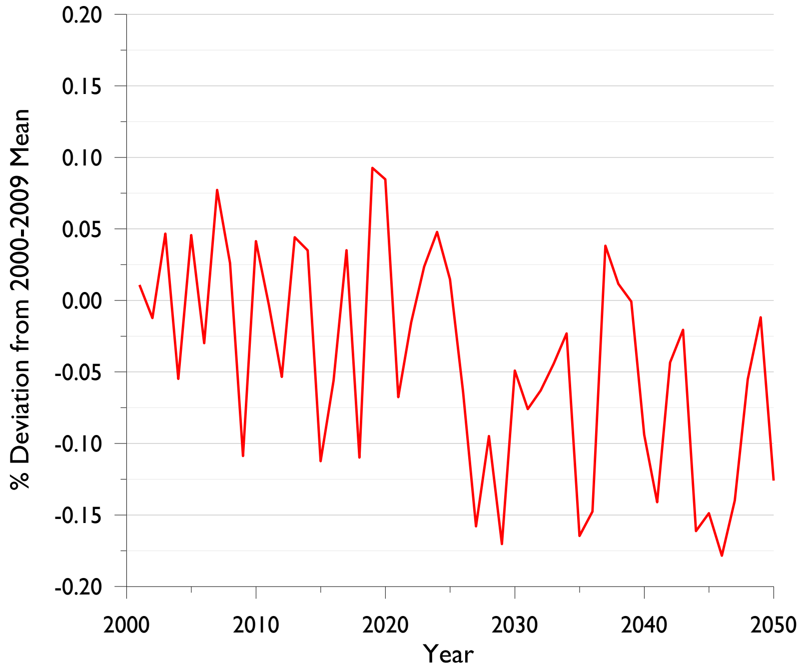

Figure 3-9. National-level motif for precipitation.

Temperature and precipitation are causally related in the climate-science sense (Trenberth et al. 2008). Historical trends appear to support increased North American precipitation, except in the Southwest (Trenberth et al. 2008), as do individual AOGCM models (Christensen et al. 2004). We have observed a similar relationship at the national-level between precipitation and temperature correlations within the model ensemble, but with greater variation than indicated in the historical data. The data points in the scatter plot of Figure 3-10 show the national-level average temperature over the 40-year period of interest compared with the national average level of precipitation of the same period for the same AOGCM model ensemble.

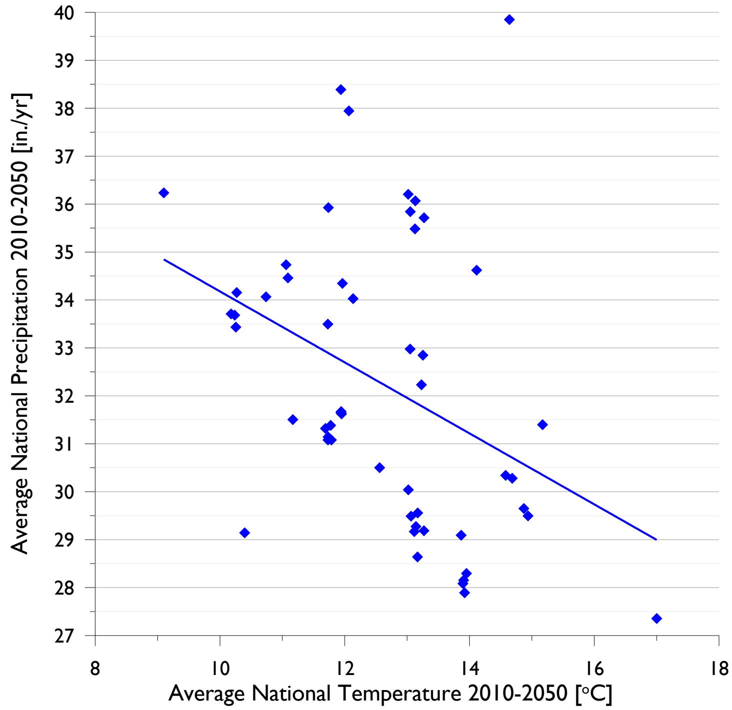

Figure 3-10. Ensemble temperature and precipitation relationship.

As an example of a simple temperature and precipitation relationship, the topmost data point in Figure 3-10 represents one of 53 model runs. The climate model that produced this data point forecasts over the 40-year analysis period an average precipitation of almost 40 inches per year and an average temperature of about 15°C. In terms of our probabilistic distribution of climatic futures for precipitation, the uppermost dot might most closely correspond to the precipitation at the 99% exceedance probability, whereas the bottommost point of around 27 inches (produced by a different climate model) would be close to our 1% exceedance probability.

Figure 3-10 demonstrates that the relationship of temperature and precipitation across all the AOGCM models in the climate ensemble we have used is complex, despite the numerical ability to generate a poorly fitting line through the data. Nonetheless, the figure has a negative slope consistent with the rising temperatures noted by Portmann et al. (2009) in the historical data. Thus, rising temperatures are, in general, associated with reductions in precipitation.

We do not adjust the temperature aspects of the motif with the sampled precipitation levels. The quantitative relation between precipitation and temperature in a U.S. state is maintained by an unchanging motif even though the precipitation is a proportional increase across all years. Any attempt to adjust the temperature in the absence of actually running the AOGCMs would have added more inconsistency in the analysis. Moreover, as discussed in the next section, temperature has a minimal effect on the total economic impacts reported.

3.2 Hydrological Impacts

We use the precipitation values in Figure 3-7 presented previously as a suitable approximation for defining reduced water conditions over a range of probabilities. The fitted gamma distribution, which is statistically estimated from the model data, includes the secondary uncertainty (as depicted in Figure 3-5); however, most of our analysis focuses on addressing the impacts along the best-estimate fit of the curve (the solid red line), which is the first-order-uncertainty.

The hydrological analysis determines the availability of water in the context of changing water supply and demand over time at the U.S. state level. The climate data from the climate-model runs describe the primary source of water via their estimated precipitation conditions. Note that these are forecasted data, not historical values. For consistency, we use as our referent the base-case forecast of the REMI macroeconomic model discussed in Section 3.3 as the basis for future economic activity that drives future water demand (usage). The hydrological model uses the time-dependent precipitation estimates to determine the adequacy of available water for the industrial activities. We then convert these availabilities of water to measures of the physical impact on industry operations and investments (as discussed in Section 3.3). Although we consider both usage and consumption, the focus here is primarily on consumption as the limiting factor. Usage and consumption are distinct concerns that are very important to hydrological analyses and the exact definition of water availability. Irrigation primarily consumes water. The cooling of thermoelectric power plants and heavy-industry facilities, as well as hydropower, is primarily a usage of water that allows further downstream consumption. Mining activities, although they extensively reuse water, are largely consumptive. Food and beverage industries are also consumptive. In determining water availability for thermoelectric generation plants, we do not count coastal facilities that operate on saline water. For agriculture, we consider irrigated and nonirrigated crop production and take into account the extremes and volatility of temperature in addition to the water conditions.

The hydrological model used in this analysis (see Appendix A) overlays a water-basin-level approach with a state-level mapping. The model determines water availability as a function of supply and demand. In broad terms, water availability becomes an issue when demand exceeds 40% to 50% of the total water supply (Taylor 2009). Demand is a composite of agricultural (irrigation and nonirrigation farming, and livestock) uses, with separate municipal, industry (as an aggregate), mining, thermoelectric generation, and hydropower needs. Chen et al. (2001) took this same modeling approach of comparing economic needs to water supply but limited the study to a specific region rather than across the whole nation.

For this analysis, we use a constant proportional relationship between precipitation and the fraction of precipitation that becomes surface water. That is, we assume that evaporation remains essentially a constant fraction of precipitation. In this study and as noted in previous studies (Arnell 1999; Seager et al. 2008), predicted precipitation has a large degree of variability compared with evaporation. Data do indicate that evaporation may increase with climate change (Golubev et al. 2001), but that would simply imply that our study underestimates the impacts of reduced precipitation due to climate change. The specification of ground-water usage is based on existing planning and policy trends (Solley et al. 1993,1998; Hutson et al. 2005; Maupin and Barber 2005) through 2050 without assuming a complete loss of ground-water resource by 2050.

Our concern is the impact of climate change relative to the macroeconomic referent. Because existing water rights are based on extensive historical precedence and are unlikely to change dramatically over the analysis time frame, a focus on that concern would detract from the primary message of the analysis. The modeling also assumes, to the extent possible, the enforcement of interstate water rights. Thus a shortage in one state, because of defined water allocations, does not necessarily result in a shortage in the downstream state.

As is common for hydrological impact analyses, this study does not take into account day-to-day fluctuations (Bates et al. 2008) although, as discussed below, intra-annual fluctuations are intrinsic to the analysis. The PCMDI ensemble does not show dramatic changes in overall CONUS precipitation over the 2010 to 2050 time horizon, and the ensemble includes simulation runs that contain both decreases and increases in precipitation at the state level. The hydrological model is assumed to be deterministic and valid for this analysis to isolate the impact of climate uncertainty. Other studies indicate the hydrological models contain less uncertainty than the climate models (Giorgi and Francisco 2000; Murphy et al. 2004).

We primarily only capture changes on a year-to-year basis in our analysis despite the resulting introduction of error. We do this to highlight major concepts, improve the understandability of results, and avoid any distraction from the primary results that would be introduced by using time scales shorter than a year. Further, the uncertainty associated with climate models has better specificity at the annual level for the latitudes of interest here (Bader et al. 2008; Dai 2006). In Section 4.3, we explore how much the annual resolution affects the simulated economic responses and damage-cost estimates.

3.2.1 Water Availability

For the agricultural impact analysis, we first develop a probability density function for the standard precipitation index (SPI) to give an indication of the drought content of the ensemble runs. The SPI is the ratio of the peak precipitation for any month in a specified area over the precipitation from a longer time period, for example, a year. We then vary the range of the SPI calculation from months to years, and we find that the SPI ranking, as relevant to the purposes here, is relatively unaffected by the choice of time interval. Subsequently, we compare the model rankings using an SPI based on one-year running averages over the 40 years of the analysis to model rankings that simply used annual precipitation. Around the 10% exceedance-probability region of the probability distribution that is our primary interest, we find that the AOGCM-simulated reductions in precipitation and increased drought (SPI) are positively correlated to a high degree. There is little or no change in the ranking of PCMDI runs using the SPI as the criterion versus using precipitation. On the one hand, this means that the use of precipitation level (average water supply) is comparable to the use of the SPI (a measure of drought conditions) for quantifying the uncertainty. On the other hand, it means we can legitimately use the SPI of the selected motif for estimating crop productivity.

The allocation of water under enduring climatic water shortages remains largely undefined. Water rights are fraught with complex legal, political, and social implications, and the legal specifics of water rights vary widely from state to state. Agriculture often has grandfathered rights to water resources, yet under the currently increasing routine instances of limited water availability, compromises, purchases, and the transfer of water rights commonly occur. In this study, we use a simple line of reasoning that assumes high-value (monetarily and politically) users can purchase water rights but only to the extent where the proportional shortage to other users, such as agriculture or mining, is twice that of the high-value users. For example, if there is an overall shortage on the order of 10%, where municipal and industry sectors experience a 7% shortfall, agriculture and mining sectors accept no more than a 14% shortfall. The difference in the allocation is associated with payments from the high-value activities to the lower-value activities to pay for the water transfer (see Section 3.2.3).

It is well beyond the scope of this study to consider the various possible scenarios that could be envisioned for water reallocation, e.g., pure market-based allocation, pro-rata sharing, or restructuring of the legal basis for water-rights allocation based on priority of use rather than on priority of right or riparian links to land. Further, we recognize that there are significant differences in water-allocation regimes between the eastern and western United States as well as among the various states. For example, we use a uniform value of $1,000 per acre-foot as the representative cost for delivered water, but this assumption of compensation reflects a market structure that does not yet exist in many U.S. locations. The consideration of marginal and average values of water costs across geographical and jurisdictional entities, many of which do not contain market mechanisms, is again well beyond the scope of this analysis. Additionally, it is impossible to determine what the unique regulatory response in each state would be to the conditions tested in this analysis (Young 2005; Changnon 2005; Schlenker et al. 2005). For these reasons, we select a middle ground that is transparent and pragmatic enough to allow an analysis, while producing acceptably realistic allocations. Frederick and Schwarz (2000) analyzed future induced water shortages and the ability to remove low-value uses. Their reported costs for water are in the range of $400 to $1,000 per acre-foot.

Some states currently have abundant water, such as Minnesota. Other states, such as New Mexico, barely have adequate water. Figure 3-11 illustrates the hydrological-model-estimated reduction in water availability in 2050 across the states for the different exceedance-probability simulations. Water availability is the estimated ratio of water demand to water supply. Figure 3-11 shows an index indicating water adequacy (or water availability) compared to the hydrological referent. A value of 1.0 means the water availability is comparable to its historical value.

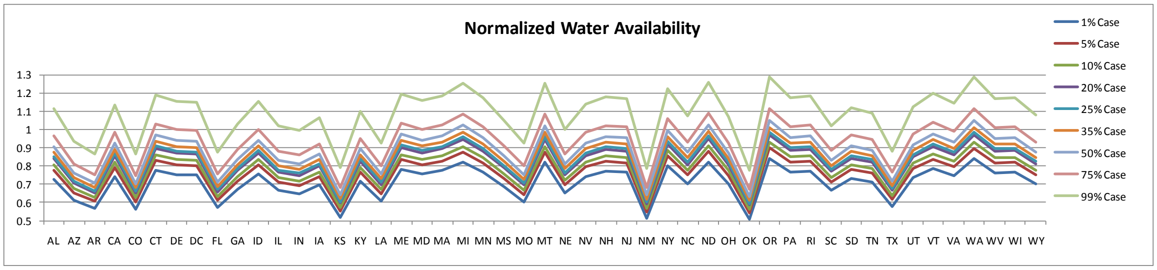

Figure 3-11. Normalized water availability (2050).

Each colored line in Figure 3-11 represents the results for a specific exceedance-probability simulation (or case), as denoted in the legend. Each colored line is actually a series of data points, with each point representing a particular state (on the y-axis) and its associated normalized water-availability value expressed as an exceedance probability (on the x-axis). The points are connected by lines to help readers visualize how water availability changes from one probability to another. Note that in all cases the water availability changes as we proceed upwards in the exceedance-probability simulations. Several examples may be helpful in interpreting the results displayed in this figure:

- The dark purple line at the bottom displays the results of the 1% exceedance-probability simulation. For Alabama, in this simulation for 2050, there is a 1% chance that Alabama will get less than 72% of its normal water. The associated data point on the top yellow line shows that there is a 99% chance that Alabama will get less than 112% of its normal water.

- The results for Kansas, with the points very close together, show little variation among the different probabilities; all results indicate less water availability. New Mexico, like Kansas, has increased water shortages in all cases. On the other hand, the state of Washington has more variation and fares much better. Even in the worst case, there is only a 1% chance that Washington will get less than 85% of its normal water in 2050.

Figure 3-12 shows the year 2050 water-availability conditions for the high-value sectors of municipalities, industry, and thermoelectric generation across the states. In this figure, the highest value on the x-axis is 1.0, indicating that all or more of the water needed is available. Because additional water does not improve economic production, the value does not exceed unity (1.0) even in flooding conditions. States that have high levels of irrigated agriculture and limited water resources, such as New Mexico, have experience adjusting to years with reduced water availability. They typically have a hierarchal process where water users with junior rights have their allocation of water restricted first. In many states, the amounts of water storage and irrigation are comparable to the water use needed for the high-value industrial and municipal water users of the economy. The economies of states that do not have significant infrastructure in place to store water or irrigated agriculture, such as South Carolina, respond sharply to reduced water availability.

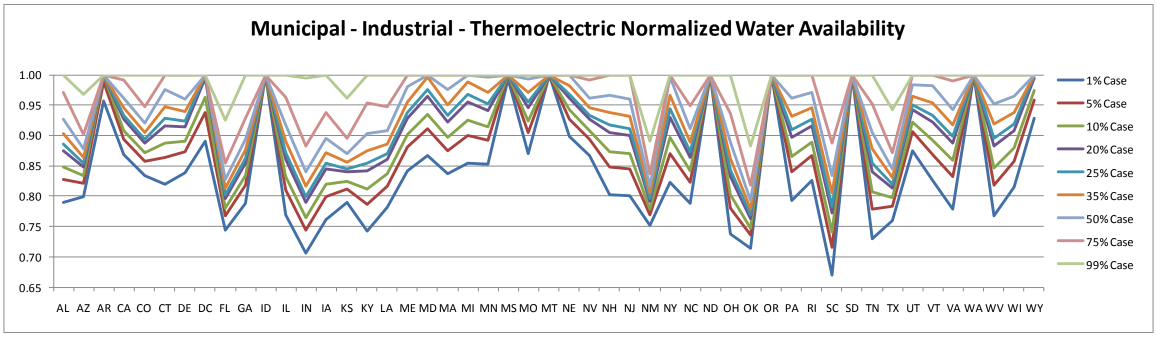

Figure 3-12. High-value-user water availability (2050).

Several examples may help in interpreting the results in Figure 3-12:

- In the best case in 2050, there is a 99% chance that Indiana will have less than 98% of the water it needs for municipal, industrial, and thermoelectric uses. In the worst case, there is a 1% chance that Indiana will have less than 70% of the water it needs for these uses, a situation that could result in shutting down power plants, for example.

- In all cases, Montana, where all the points converge at the 1.0 level, has no potential threat of a water shortage that would affect municipal, industrial, and thermoelectric uses.

Mining is very susceptible to water availability (Morrison et al. 2009). As a producer of raw material, mining has a lower value-added component than other industries (Goldsmith and Burkitt 2009) and could potentially improve its economic situation by selling its water rights. The consequences to its production levels in 2050 are shown in Figure 3-13. In the simulations, agricultural irrigation experiences the same level of shortage as mining (in return for water payments). As an example from the figure, there is a 50% chance that mining in Florida in 2050 will receive less than 68% of the water it needs for operations. In all instances, lower probabilities indicate a progressively worse predicament.

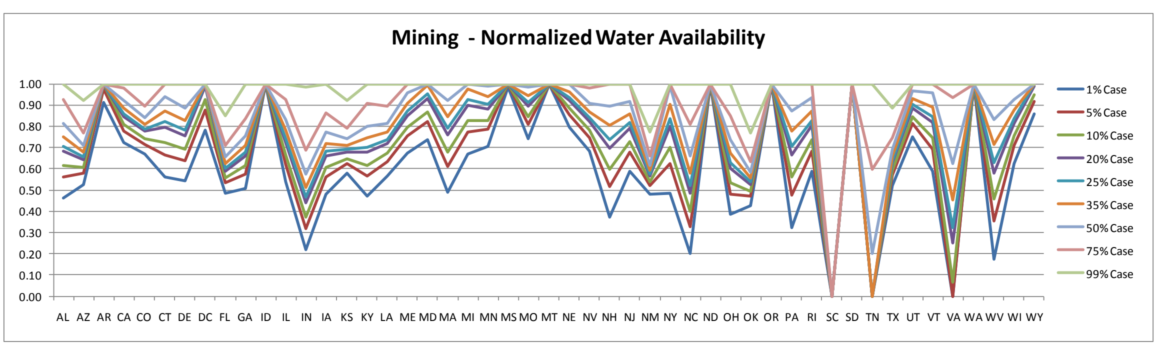

Figure 3-13. Mining water availability (2050).

Figure 3-14 conforms largely to Figure 3-11 and shows the impact of water availability (for usage) on hydroelectric generation in 2050 as a function of exceedance probability. In states with a strong interconnection between water used for hydroelectric power and consumption (primarily agriculture) such as New Mexico and Kansas, hydroelectric generation is affected more drastically than in other states.

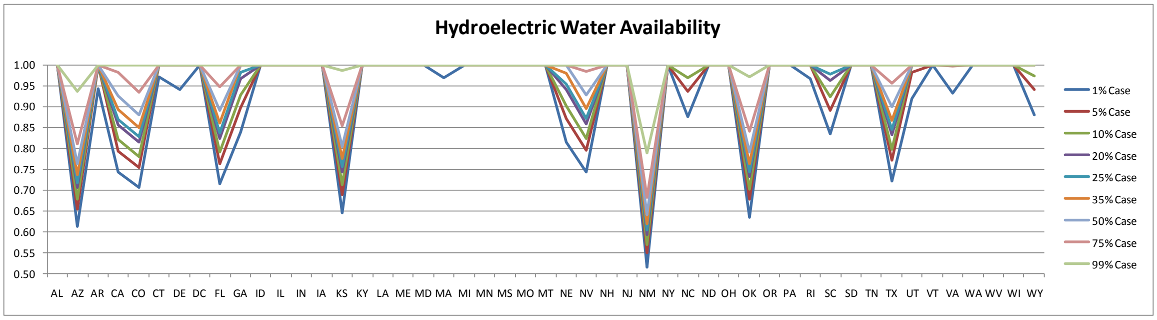

Figure 3-14. Hydroelectric water availability (2050).

The next series of figures (3-15 through 3-20) show the interannual volitility in water availability at the 50%, 10%, and 1% exceedance probabilities. The shading goes from green (adequate water availability) to yellow (diminished availability) to red (significant shortages) to demonstrate how the volatility changes from year to year and causes more acute conditions at the lower exceedance probabilities, i.e., less than 50%.

Figure 3-15 and Figure 3-16 show the 50% exceedance-probability water availability for the high-value economic components and mining, respectively. The core economy encounters only modest concerns about water availability at this exceedance probability. The analysis, however, shows that mining has some years where its production would be affected. For example, Figure 3-15 shows West Virgina industry having only scattered water-availability concerns beyond 2040. Figure 3-16 indicates much greater water-availability challenges for West Virgina mining, with water availability occasionally dipping below 50%.

Figure 3-17 and Figure 3-18 show the 10% exceedance-probability conditions, and Figure 3-19 and Figure 3-20 show the 1% exceedance-probability conditions. For Massachusetts, at the 10% exceedance probability, there are many more instances of reduced water availablity than at the 50% exceedance probability. At the 1% exceedance probability, the Massachusetts economy experiences reduced water availability over most years. Figure 3-20 shows that by 2030 and increasing through 2050, mining would experience significant shortages in many states.

Year	AL	AZ	AR	CA	CO	CT	DE	DC	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
2010	1.000	0.979	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.976	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2013	1.000	1.000	1.000	0.960	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2014	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	1.000	0.853	1.000	0.894	0.925	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.948	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2016	1.000	0.796	1.000	0.831	1.000	1.000	1.000	1.000	1.000	0.932	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2017	1.000	0.985	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2018	1.000	0.840	1.000	0.931	1.000	1.000	1.000	1.000	0.969	0.988	1.000	1.000	1.000	1.000	0.954	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2019	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2021	1.000	0.801	1.000	0.856	1.000	1.000	0.983	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2022	1.000	0.978	1.000	1.000	1.000	1.000	1.000	1.000	0.994	0.980	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2023	1.000	0.799	1.000	1.000	1.000	0.949	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.890	1.000	1.000	1.000	1.000	1.000
2024	1.000	1.000	1.000	0.950	1.000	1.000	1.000	1.000	0.956	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.964	1.000	1.000	1.000	1.000	1.000
2025	1.000	0.903	1.000	0.922	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2026	1.000	0.822	1.000	0.811	1.000	0.994	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.998	1.000	1.000	1.000	1.000	1.000
2027	0.899	0.902	1.000	0.724	1.000	1.000	0.920	1.000	0.887	0.819	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2028	0.966	0.954	1.000	0.946	1.000	0.978	0.962	1.000	1.000	0.937	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.981	1.000	1.000	1.000	1.000	1.000
2029	1.000	0.838	1.000	0.813	0.926	0.957	0.923	1.000	0.960	0.912	1.000	1.000	1.000	1.000	0.967	1.000	1.000	1.000	1.000	0.984	1.000	1.000	1.000	1.000	1.000
2030	1.000	0.883	1.000	1.000	0.987	0.951	0.964	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.978	1.000	1.000	1.000	1.000	1.000
2031	0.960	0.971	1.000	0.925	1.000	1.000	1.000	1.000	0.981	0.877	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2032	1.000	0.988	1.000	0.995	1.000	0.985	1.000	1.000	1.000	1.000	1.000	1.000	0.998	1.000	1.000	1.000	1.000	1.000	1.000	0.987	1.000	1.000	1.000	1.000	1.000
2033	0.905	0.973	1.000	1.000	1.000	1.000	1.000	1.000	0.988	0.859	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2034	1.000	0.949	1.000	0.907	1.000	1.000	1.000	1.000	0.960	0.955	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2035	0.944	0.869	1.000	0.846	1.000	0.844	0.945	1.000	1.000	0.935	1.000	0.999	0.908	0.980	0.889	1.000	1.000	1.000	1.000	0.874	1.000	1.000	1.000	0.961	1.000
2036	0.946	0.832	1.000	0.815	0.931	1.000	0.980	1.000	0.957	0.900	1.000	1.000	0.898	0.886	0.909	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2037	1.000	0.771	1.000	0.807	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.986	0.986	1.000	1.000	1.000
2038	0.930	0.829	1.000	0.879	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.985	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.949	1.000	1.000	1.000
2039	1.000	1.000	1.000	0.893	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.932	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2040	0.865	0.734	1.000	0.746	0.944	0.956	0.967	1.000	1.000	0.922	1.000	1.000	0.932	1.000	1.000	1.000	1.000	1.000	1.000	0.985	1.000	1.000	1.000	1.000	1.000
2041	0.919	0.886	1.000	0.796	0.989	0.994	0.936	1.000	0.990	0.952	1.000	1.000	0.905	0.916	0.974	0.884	1.000	1.000	1.000	1.000	1.000	0.925	1.000	1.000	1.000
2042	0.925	0.804	1.000	1.000	1.000	1.000	0.931	1.000	0.952	0.986	1.000	1.000	0.964	0.955	1.000	1.000	1.000	1.000	1.000	1.000	0.965	1.000	1.000	1.000	1.000
2043	1.000	0.834	1.000	0.904	0.936	1.000	1.000	1.000	0.903	0.963	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2044	0.935	0.712	1.000	0.780	0.967	1.000	1.000	1.000	1.000	0.979	1.000	0.920	0.844	0.878	1.000	0.965	0.989	0.970	1.000	1.000	0.899	1.000	1.000	1.000	1.000
2045	0.759	0.982	1.000	0.791	1.000	0.944	0.880	0.922	0.774	0.765	1.000	1.000	0.903	0.908	0.913	0.909	0.979	1.000	0.951	1.000	1.000	1.000	1.000	1.000	1.000
2046	0.893	0.932	1.000	0.866	0.989	0.994	0.971	1.000	0.781	0.926	1.000	0.852	0.815	0.729	0.913	0.953	0.914	1.000	1.000	0.996	0.753	0.811	1.000	0.997	1.000
2047	0.816	0.958	1.000	0.956	1.000	0.984	0.949	1.000	0.924	0.871	1.000	0.817	0.752	0.770	0.879	0.695	0.868	1.000	1.000	1.000	0.859	0.838	1.000	0.919	1.000
2048	0.872	1.000	1.000	1.000	1.000	1.000	0.975	1.000	0.850	0.845	1.000	0.841	0.803	0.817	0.973	0.839	0.961	1.000	1.000	1.000	0.839	1.000	1.000	0.994	1.000
2049	0.885	0.917	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.923	1.000	1.000	0.980	1.000	1.000	1.000	0.902	1.000	1.000	0.997	0.946	1.000	1.000	1.000	1.000
2050	0.927	0.877	1.000	0.961	0.920	0.975	0.960	1.000	0.828	0.894	1.000	0.917	0.840	0.895	0.869	0.903	0.907	0.980	1.000	0.975	1.000	0.995	1.000	0.992	1.000

Year	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
2010	1.000	1.000	1.000	1.000	0.988	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	1.000	1.000	1.000	0.988	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000
2013	1.000	0.976	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.984	1.000	1.000	1.000	1.000
2014	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	0.981	0.868	1.000	1.000	0.839	1.000	1.000	1.000	1.000	0.937	1.000	1.000	1.000	0.983	1.000	1.000	0.962	0.982	1.000	0.995	1.000	1.000	1.000	1.000
2016	1.000	0.803	1.000	1.000	0.907	1.000	0.921	1.000	1.000	1.000	1.000	1.000	1.000	0.849	1.000	1.000	1.000	0.938	1.000	1.000	1.000	1.000	1.000	1.000
2017	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.955	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2018	0.980	0.959	1.000	1.000	0.865	1.000	1.000	1.000	1.000	0.917	1.000	1.000	1.000	0.959	1.000	1.000	0.977	1.000	1.000	0.922	1.000	1.000	1.000	1.000
2019	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000	1.000	0.983	1.000	1.000	1.000	1.000
2021	1.000	0.876	1.000	1.000	0.888	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.935	1.000	0.957	1.000	1.000	1.000	1.000
2022	1.000	1.000	1.000	1.000	0.893	1.000	0.948	1.000	1.000	1.000	1.000	1.000	1.000	0.893	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2023	1.000	1.000	1.000	1.000	0.840	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.976	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2024	1.000	0.924	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2025	1.000	0.889	1.000	1.000	0.972	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2026	1.000	0.817	1.000	1.000	0.911	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.972	1.000	1.000	1.000	1.000	1.000	1.000
2027	1.000	0.745	1.000	1.000	0.932	1.000	0.851	1.000	1.000	1.000	0.958	1.000	1.000	0.781	1.000	0.934	1.000	0.976	1.000	0.874	1.000	1.000	1.000	1.000
2028	1.000	0.944	1.000	1.000	0.849	1.000	0.935	1.000	1.000	0.934	1.000	1.000	1.000	0.942	1.000	0.911	0.812	1.000	1.000	0.908	1.000	1.000	1.000	1.000
2029	1.000	0.791	1.000	1.000	0.784	1.000	0.935	1.000	1.000	0.959	1.000	1.000	0.968	0.876	1.000	0.864	1.000	0.876	1.000	0.847	1.000	0.958	1.000	0.974
2030	1.000	1.000	1.000	1.000	0.792	1.000	0.951	1.000	1.000	0.924	1.000	1.000	1.000	0.987	1.000	1.000	0.886	1.000	1.000	0.931	1.000	1.000	1.000	1.000
2031	1.000	0.968	1.000	1.000	0.901	1.000	0.905	1.000	1.000	0.970	1.000	1.000	1.000	0.846	1.000	0.925	0.857	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2032	1.000	0.964	1.000	1.000	0.944	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.979	1.000	1.000	0.918	1.000	1.000	1.000	0.990	1.000	1.000	1.000	1.000
2033	1.000	1.000	1.000	1.000	0.898	1.000	0.983	1.000	1.000	0.908	1.000	1.000	1.000	0.907	1.000	0.848	0.965	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2034	1.000	0.863	1.000	1.000	0.996	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.993	1.000	1.000	1.000	0.970	1.000	1.000	1.000	1.000	1.000	0.983
2035	1.000	0.870	0.862	0.957	0.838	0.842	0.998	1.000	0.977	0.771	1.000	0.865	0.848	0.981	1.000	0.877	0.774	1.000	0.947	0.957	1.000	0.926	1.000	1.000
2036	0.955	0.856	1.000	1.000	0.867	1.000	0.956	1.000	0.959	0.914	1.000	0.968	1.000	0.924	1.000	0.885	0.966	0.954	1.000	0.967	1.000	0.937	1.000	1.000
2037	1.000	0.869	1.000	1.000	0.905	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.956	1.000	1.000	1.000	1.000	1.000	1.000
2038	1.000	0.925	1.000	1.000	0.941	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.991	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2039	1.000	0.972	1.000	1.000	0.954	1.000	1.000	1.000	0.973	0.927	1.000	0.970	0.997	1.000	1.000	0.985	0.963	1.000	1.000	1.000	1.000	0.996	1.000	1.000
2040	1.000	0.770	0.990	1.000	0.800	0.977	0.905	1.000	0.937	1.000	1.000	0.948	0.951	0.897	1.000	0.839	1.000	0.889	0.991	0.938	1.000	0.908	1.000	1.000
2041	0.958	0.818	1.000	0.992	0.920	1.000	0.917	0.987	0.898	0.965	1.000	0.909	1.000	0.906	1.000	0.864	0.944	0.976	1.000	0.851	1.000	0.795	1.000	1.000
2042	1.000	0.959	1.000	1.000	0.908	1.000	0.952	1.000	0.940	1.000	1.000	0.939	0.997	0.974	1.000	0.924	0.999	0.919	1.000	0.872	1.000	0.861	0.999	1.000
2043	1.000	0.913	1.000	1.000	0.851	1.000	0.965	1.000	0.917	1.000	1.000	0.934	1.000	0.917	1.000	1.000	1.000	0.924	1.000	0.953	1.000	0.900	1.000	1.000
2044	1.000	0.787	0.979	1.000	0.844	1.000	0.916	1.000	0.944	0.865	1.000	1.000	1.000	0.910	1.000	0.897	0.855	0.841	1.000	0.976	1.000	0.993	0.917	1.000
2045	0.952	0.826	1.000	0.921	0.986	0.998	0.775	1.000	0.871	0.973	1.000	0.888	0.949	0.700	1.000	0.840	1.000	0.993	1.000	0.804	1.000	0.799	1.000	1.000
2046	0.936	0.842	0.996	0.957	0.888	0.955	0.933	1.000	0.889	0.839	1.000	0.923	1.000	0.911	1.000	0.940	0.870	0.946	0.999	0.949	1.000	0.958	0.777	1.000
2047	0.949	0.975	1.000	0.902	0.969	1.000	0.932	1.000	0.804	0.792	1.000	0.864	1.000	0.843	1.000	0.763	0.864	0.986	1.000	0.895	1.000	0.824	0.796	1.000
2048	1.000	1.000	1.000	0.959	0.908	1.000	0.895	1.000	0.838	0.878	1.000	0.894	1.000	0.803	1.000	0.900	0.997	1.000	1.000	0.933	1.000	0.868	0.871	1.000
2049	1.000	1.000	1.000	0.992	0.924	0.938	1.000	1.000	0.921	0.956	1.000	0.925	0.988	0.989	1.000	0.900	0.932	1.000	0.989	1.000	1.000	0.964	0.966	1.000
2050	0.999	0.962	0.967	0.960	0.816	0.997	0.911	1.000	0.889	0.792	1.000	0.961	0.971	0.834	1.000	0.904	0.845	0.984	0.981	0.943	1.000	0.952	0.964	1.000

Figure 3-15. Water availability (municipal, industrial, themoelectric – 50% exceedance probability).

Year	AL	AZ	AR	CA	CO	CT	DE	DC	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
2010	1.000	0.958	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.953	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2013	1.000	1.000	1.000	0.920	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2014	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	1.000	0.701	1.000	0.788	0.850	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.896	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2016	1.000	0.585	1.000	0.660	1.000	1.000	1.000	1.000	1.000	0.863	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2017	1.000	0.968	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2018	1.000	0.673	1.000	0.862	1.000	1.000	1.000	1.000	0.938	0.976	1.000	1.000	1.000	1.000	0.908	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2019	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2021	1.000	0.590	1.000	0.711	1.000	1.000	0.966	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2022	1.000	0.954	1.000	1.000	1.000	1.000	1.000	1.000	0.987	0.961	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2023	1.000	0.582	1.000	1.000	1.000	0.898	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.780	1.000	1.000	1.000	1.000	1.000
2024	1.000	1.000	1.000	0.899	1.000	1.000	1.000	1.000	0.912	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.929	1.000	1.000	1.000	1.000	1.000
2025	1.000	0.799	1.000	0.842	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2026	1.000	0.628	1.000	0.617	1.000	0.988	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.996	1.000	1.000	1.000	1.000	1.000
2027	0.798	0.794	1.000	0.440	1.000	1.000	0.839	1.000	0.774	0.638	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2028	0.932	0.903	1.000	0.890	1.000	0.956	0.923	1.000	1.000	0.874	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.960	1.000	1.000	1.000	1.000	1.000
2029	1.000	0.657	1.000	0.621	0.851	0.912	0.843	1.000	0.921	0.824	1.000	1.000	1.000	1.000	0.934	1.000	1.000	1.000	1.000	0.966	1.000	1.000	1.000	1.000	1.000
2030	1.000	0.753	1.000	1.000	0.974	0.898	0.925	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.954	1.000	1.000	1.000	1.000	1.000
2031	0.920	0.939	1.000	0.847	1.000	1.000	1.000	1.000	0.962	0.755	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2032	1.000	0.974	1.000	0.991	1.000	0.967	1.000	1.000	1.000	1.000	1.000	1.000	0.996	1.000	1.000	1.000	1.000	1.000	1.000	0.972	1.000	1.000	1.000	1.000	1.000
2033	0.810	0.943	1.000	1.000	1.000	1.000	1.000	1.000	0.977	0.718	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2034	1.000	0.890	1.000	0.811	1.000	1.000	1.000	1.000	0.920	0.909	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2035	0.889	0.716	1.000	0.686	1.000	0.662	0.880	1.000	1.000	0.868	1.000	0.998	0.815	0.960	0.778	1.000	1.000	1.000	1.000	0.708	1.000	1.000	1.000	0.922	1.000
2036	0.891	0.636	1.000	0.623	0.861	1.000	0.956	1.000	0.914	0.794	1.000	1.000	0.795	0.772	0.818	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2037	1.000	0.500	1.000	0.606	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.972	0.972	1.000	1.000	1.000
2038	0.860	0.624	1.000	0.752	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.969	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.899	1.000	1.000	1.000
2039	1.000	1.000	1.000	0.781	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.863	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2040	0.721	0.410	1.000	0.477	0.888	0.899	0.923	1.000	1.000	0.836	1.000	1.000	0.859	1.000	1.000	1.000	1.000	1.000	1.000	0.961	1.000	1.000	1.000	1.000	1.000
2041	0.829	0.745	1.000	0.580	0.978	0.987	0.846	1.000	0.980	0.897	1.000	1.000	0.799	0.832	0.948	0.769	1.000	1.000	1.000	1.000	1.000	0.850	1.000	1.000	1.000
2042	0.840	0.560	1.000	1.000	1.000	1.000	0.832	1.000	0.904	0.969	1.000	1.000	0.922	0.909	1.000	1.000	1.000	1.000	1.000	1.000	0.930	1.000	1.000	1.000	1.000
2043	1.000	0.627	1.000	0.802	0.872	1.000	1.000	1.000	0.806	0.919	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2044	0.856	0.345	1.000	0.546	0.935	1.000	1.000	1.000	1.000	0.954	1.000	0.839	0.647	0.755	1.000	0.929	0.978	0.941	1.000	1.000	0.794	1.000	1.000	1.000	1.000
2045	0.452	0.958	1.000	0.568	1.000	0.869	0.695	0.844	0.547	0.479	1.000	1.000	0.776	0.814	0.827	0.817	0.958	1.000	0.902	1.000	1.000	1.000	1.000	1.000	1.000
2046	0.751	0.844	1.000	0.723	0.978	0.986	0.924	1.000	0.562	0.834	1.000	0.705	0.562	0.445	0.826	0.906	0.829	1.000	1.000	0.990	0.480	0.622	1.000	0.995	1.000
2047	0.563	0.903	1.000	0.909	1.000	0.961	0.865	1.000	0.847	0.710	1.000	0.635	0.396	0.523	0.757	0.390	0.736	1.000	1.000	1.000	0.697	0.676	1.000	0.837	1.000
2048	0.689	1.000	1.000	1.000	1.000	1.000	0.933	1.000	0.700	0.647	1.000	0.681	0.507	0.615	0.947	0.677	0.921	1.000	1.000	1.000	0.647	1.000	1.000	0.989	1.000
2049	0.713	0.806	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.823	1.000	1.000	0.949	1.000	1.000	1.000	0.804	1.000	1.000	0.991	0.880	1.000	1.000	1.000	1.000
2050	0.814	0.710	1.000	0.919	0.840	0.939	0.887	1.000	0.654	0.755	1.000	0.833	0.574	0.771	0.739	0.801	0.815	0.959	1.000	0.921	1.000	0.991	1.000	0.984	1.000

Year	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
2010	1.000	1.000	1.000	1.000	0.976	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	1.000	1.000	1.000	0.977	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.998	1.000	1.000	1.000	1.000
2013	1.000	0.952	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.968	1.000	1.000	1.000	1.000
2014	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	0.962	0.729	1.000	1.000	0.678	1.000	1.000	1.000	1.000	0.874	1.000	1.000	1.000	0.966	1.000	1.000	0.924	0.964	1.000	0.989	1.000	1.000	1.000	1.000
2016	1.000	0.595	1.000	1.000	0.814	1.000	0.843	1.000	1.000	1.000	1.000	1.000	1.000	0.697	1.000	1.000	1.000	0.876	1.000	1.000	1.000	1.000	1.000	1.000
2017	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.909	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2018	0.960	0.916	1.000	1.000	0.727	1.000	1.000	1.000	1.000	0.833	1.000	1.000	1.000	0.918	1.000	1.000	0.953	1.000	1.000	0.844	1.000	1.000	1.000	1.000
2019	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.998	1.000	1.000	1.000	1.000	1.000	1.000	0.965	1.000	1.000	1.000	1.000
2021	1.000	0.741	1.000	1.000	0.774	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.871	1.000	0.910	1.000	1.000	1.000	1.000
2022	1.000	1.000	1.000	1.000	0.784	1.000	0.895	1.000	1.000	1.000	1.000	1.000	1.000	0.774	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2023	1.000	1.000	1.000	1.000	0.677	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.953	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2024	1.000	0.839	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2025	1.000	0.763	1.000	1.000	0.943	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2026	1.000	0.609	1.000	1.000	0.819	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.944	1.000	1.000	1.000	1.000	1.000	1.000
2027	1.000	0.455	1.000	1.000	0.862	1.000	0.686	1.000	1.000	1.000	0.916	1.000	1.000	0.478	1.000	0.868	1.000	0.952	1.000	0.703	1.000	1.000	1.000	1.000
2028	1.000	0.879	1.000	1.000	0.693	1.000	0.861	1.000	1.000	0.867	1.000	1.000	1.000	0.858	1.000	0.822	0.624	1.000	1.000	0.777	1.000	1.000	1.000	1.000
2029	1.000	0.550	1.000	1.000	0.562	1.000	0.858	1.000	1.000	0.918	1.000	1.000	0.936	0.686	1.000	0.722	1.000	0.751	1.000	0.620	1.000	0.917	1.000	0.948
2030	1.000	1.000	1.000	1.000	0.577	1.000	0.892	1.000	1.000	0.849	1.000	1.000	1.000	0.967	1.000	1.000	0.773	1.000	1.000	0.823	1.000	1.000	1.000	1.000
2031	1.000	0.931	1.000	1.000	0.798	1.000	0.787	1.000	1.000	0.940	1.000	1.000	1.000	0.580	1.000	0.839	0.715	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2032	1.000	0.921	1.000	1.000	0.887	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.958	1.000	1.000	0.818	1.000	1.000	1.000	0.972	1.000	1.000	1.000	1.000
2033	1.000	1.000	1.000	1.000	0.793	1.000	0.960	1.000	1.000	0.816	1.000	1.000	1.000	0.724	1.000	0.652	0.930	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2034	1.000	0.699	1.000	1.000	0.992	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.979	1.000	1.000	1.000	0.939	1.000	1.000	1.000	1.000	1.000	0.967
2035	1.000	0.713	0.715	0.913	0.670	0.678	0.995	1.000	0.954	0.543	1.000	0.720	0.689	0.939	1.000	0.697	0.547	1.000	0.895	0.870	1.000	0.852	1.000	1.000
2036	0.911	0.680	1.000	1.000	0.728	1.000	0.892	1.000	0.917	0.829	1.000	0.933	1.000	0.739	1.000	0.706	0.931	0.907	1.000	0.896	1.000	0.872	1.000	1.000
2037	1.000	0.707	1.000	1.000	0.806	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.912	1.000	1.000	1.000	1.000	1.000	1.000
2038	1.000	0.832	1.000	1.000	0.880	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.975	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2039	1.000	0.937	1.000	1.000	0.906	1.000	1.000	1.000	0.946	0.853	1.000	0.930	0.994	1.000	1.000	0.956	0.926	1.000	1.000	1.000	1.000	0.992	1.000	1.000
2040	1.000	0.480	0.977	1.000	0.590	0.947	0.745	1.000	0.874	1.000	1.000	0.877	0.895	0.536	1.000	0.497	1.000	0.778	0.982	0.773	1.000	0.789	1.000	1.000
2041	0.917	0.587	1.000	0.985	0.836	1.000	0.770	0.974	0.796	0.930	1.000	0.779	1.000	0.541	1.000	0.549	0.888	0.951	1.000	0.425	1.000	0.515	1.000	1.000
2042	1.000	0.906	1.000	1.000	0.810	1.000	0.863	1.000	0.878	1.000	1.000	0.847	0.995	0.863	1.000	0.734	0.997	0.838	1.000	0.484	1.000	0.660	0.999	1.000
2043	1.000	0.801	1.000	1.000	0.692	1.000	0.897	1.000	0.830	1.000	1.000	0.830	1.000	0.502	1.000	1.000	1.000	0.849	1.000	0.799	1.000	0.746	1.000	1.000
2044	1.000	0.509	0.947	1.000	0.678	1.000	0.747	1.000	0.883	0.730	1.000	1.000	1.000	0.390	1.000	0.581	0.710	0.682	1.000	0.891	1.000	0.981	0.834	1.000
2045	0.904	0.596	1.000	0.842	0.970	0.995	0.298	1.000	0.726	0.945	1.000	0.696	0.885	0.000	1.000	0.290	1.000	0.987	1.000	0.072	1.000	0.447	1.000	1.000
2046	0.872	0.630	0.989	0.914	0.769	0.883	0.785	1.000	0.759	0.678	1.000	0.783	1.000	0.179	1.000	0.708	0.740	0.892	0.999	0.743	1.000	0.879	0.554	1.000
2047	0.897	0.942	1.000	0.801	0.935	1.000	0.772	1.000	0.568	0.585	1.000	0.605	1.000	0.000	1.000	0.000	0.727	0.972	1.000	0.439	1.000	0.470	0.592	1.000
2048	1.000	1.000	1.000	0.915	0.808	1.000	0.636	1.000	0.635	0.755	1.000	0.680	1.000	0.000	1.000	0.387	0.994	1.000	1.000	0.620	1.000	0.581	0.743	1.000
2049	1.000	1.000	0.999	0.983	0.842	0.825	1.000	1.000	0.819	0.912	1.000	0.765	0.971	0.753	1.000	0.294	0.863	1.000	0.974	1.000	1.000	0.879	0.932	1.000
2050	0.998	0.909	0.894	0.917	0.617	0.990	0.661	1.000	0.738	0.585	1.000	0.873	0.933	0.000	1.000	0.199	0.690	0.967	0.956	0.624	1.000	0.829	0.928	1.000

Figure 3-16. Water availability (mining – 50% exceedance probability).

Year	AL	AZ	AR	CA	CO	CT	DE	DC	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
2010	1.000	0.969	1.000	1.000	1.000	0.987	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	0.977	1.000	0.989	1.000	1.000	1.000	1.000	1.000	0.995	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.944	1.000	0.994	0.993	0.992	0.983	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.994	1.000	1.000	1.000	1.000	0.993	1.000	1.000	1.000	1.000	1.000
2013	1.000	1.000	1.000	0.919	1.000	0.964	0.955	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.987	1.000	1.000	1.000	1.000	1.000
2014	1.000	1.000	1.000	0.948	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.959	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	1.000	0.810	1.000	0.849	0.876	1.000	0.988	1.000	1.000	0.951	1.000	1.000	1.000	1.000	0.895	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2016	1.000	0.760	1.000	0.792	1.000	0.943	0.979	1.000	0.944	0.871	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000
2017	1.000	0.927	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.979	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2018	1.000	0.799	1.000	0.881	0.964	0.964	0.966	1.000	0.910	0.920	1.000	1.000	1.000	1.000	0.901	1.000	1.000	1.000	1.000	0.950	1.000	1.000	1.000	1.000	1.000
2019	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.000	1.000	1.000	0.998	1.000	0.936	0.977	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.949	1.000	1.000	1.000	1.000	1.000
2021	1.000	0.765	1.000	0.815	0.985	0.927	0.913	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.942	1.000	1.000	1.000	1.000	1.000
2022	1.000	0.921	1.000	0.962	0.996	1.000	1.000	1.000	0.931	0.913	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.972	1.000	1.000	1.000	1.000	1.000
2023	1.000	0.762	1.000	1.000	1.000	0.864	0.954	1.000	1.000	0.983	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.821	1.000	1.000	1.000	1.000	1.000
2024	1.000	0.963	1.000	0.898	1.000	0.962	1.000	1.000	0.897	0.958	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.887	1.000	1.000	1.000	1.000	1.000
2025	1.000	0.855	1.000	0.873	1.000	0.962	0.974	1.000	1.000	0.972	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.991	1.000	1.000	1.000	1.000	1.000
2026	1.000	0.783	1.000	0.775	1.000	0.904	0.966	1.000	1.000	0.953	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	1.000	1.000	1.000	1.000
2027	0.828	0.854	1.000	0.697	1.000	0.918	0.855	1.000	0.835	0.768	0.967	1.000	1.000	1.000	1.000	1.000	0.949	1.000	1.000	0.976	1.000	1.000	1.000	1.000	1.000
2028	0.887	0.900	1.000	0.894	1.000	0.890	0.893	1.000	1.000	0.873	1.000	1.000	1.000	1.000	0.997	1.000	0.948	1.000	1.000	0.902	1.000	1.000	1.000	1.000	1.000
2029	0.961	0.797	1.000	0.777	0.877	0.871	0.858	1.000	0.900	0.850	1.000	1.000	1.000	1.000	0.912	0.990	1.000	1.000	1.000	0.905	1.000	1.000	1.000	1.000	1.000
2030	1.000	0.838	1.000	0.945	0.931	0.865	0.894	1.000	1.000	0.988	1.000	1.000	0.969	0.997	1.000	1.000	1.000	1.000	1.000	0.900	1.000	1.000	1.000	1.000	1.000
2031	0.880	0.916	1.000	0.875	0.989	0.971	0.935	1.000	0.918	0.819	1.000	1.000	1.000	0.982	0.945	1.000	1.000	1.000	1.000	0.979	1.000	0.978	1.000	1.000	1.000
2032	0.987	0.930	1.000	0.938	1.000	0.895	0.950	1.000	1.000	0.939	1.000	0.992	0.905	0.957	1.000	1.000	1.000	1.000	1.000	0.907	1.000	0.988	1.000	1.000	1.000
2033	0.831	0.917	1.000	1.000	0.981	0.957	0.955	1.000	0.925	0.803	1.000	1.000	0.911	1.000	0.948	1.000	1.000	1.000	1.000	0.992	1.000	1.000	1.000	1.000	1.000
2034	0.928	0.896	1.000	0.860	1.000	1.000	1.000	1.000	0.899	0.887	1.000	1.000	1.000	0.982	1.000	1.000	1.000	1.000	1.000	0.995	0.923	1.000	1.000	1.000	1.000
2035	0.865	0.825	0.960	0.806	0.951	0.770	0.878	1.000	1.000	0.870	1.000	0.908	0.824	0.897	0.842	0.948	0.959	0.989	1.000	0.807	0.947	1.000	1.000	0.898	1.000
2036	0.866	0.792	1.000	0.779	0.881	0.964	0.909	1.000	0.896	0.838	1.000	0.943	0.815	0.814	0.860	0.925	1.000	1.000	1.000	1.000	1.000	0.981	1.000	1.000	1.000
2037	1.000	0.738	1.000	0.772	0.996	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.933	1.000	1.000	1.000	1.000	1.000	1.000	0.898	0.908	1.000	1.000	1.000
2038	0.851	0.789	1.000	0.835	1.000	1.000	1.000	1.000	0.952	0.932	1.000	1.000	0.970	0.900	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.876	1.000	1.000	1.000
2039	0.980	0.999	1.000	0.848	1.000	0.933	0.959	1.000	1.000	1.000	1.000	1.000	0.845	0.966	0.974	0.944	1.000	0.995	1.000	0.962	1.000	0.962	1.000	1.000	1.000
2040	0.793	0.705	1.000	0.717	0.893	0.870	0.897	1.000	0.991	0.858	1.000	1.000	0.845	0.988	0.984	0.921	1.000	0.975	1.000	0.905	0.964	1.000	1.000	1.000	1.000
2041	0.841	0.840	1.000	0.761	0.932	0.904	0.869	0.960	0.925	0.885	1.000	0.947	0.821	0.839	0.917	0.796	0.926	1.000	0.955	0.961	0.941	0.853	1.000	1.000	1.000
2042	0.847	0.767	1.000	0.988	0.962	0.930	0.865	0.933	0.891	0.915	1.000	1.000	0.874	0.873	1.000	0.954	0.947	1.000	0.949	0.995	0.878	0.962	1.000	1.000	1.000
2043	0.958	0.795	1.000	0.857	0.886	0.972	0.929	1.000	0.847	0.894	1.000	1.000	0.916	0.977	1.000	0.910	1.000	1.000	1.000	0.978	0.991	1.000	1.000	1.000	1.000
2044	0.855	0.686	1.000	0.748	0.913	0.930	0.954	1.000	0.982	0.909	1.000	0.836	0.767	0.804	0.951	0.867	0.911	0.894	1.000	0.920	0.819	0.929	1.000	0.946	1.000
2045	0.699	0.925	1.000	0.757	0.998	0.860	0.820	0.842	0.732	0.719	1.000	0.938	0.820	0.830	0.863	0.817	0.901	0.937	0.871	0.920	0.957	0.933	1.000	1.000	1.000
2046	0.818	0.882	1.000	0.824	0.932	0.904	0.901	1.000	0.739	0.861	1.000	0.776	0.742	0.672	0.863	0.856	0.844	1.000	0.965	0.916	0.690	0.751	1.000	0.928	1.000
2047	0.750	0.905	0.975	0.903	0.944	0.894	0.881	0.998	0.865	0.813	1.000	0.745	0.686	0.708	0.833	0.627	0.802	1.000	0.930	1.000	0.783	0.775	0.942	0.858	1.000
2048	0.799	0.984	1.000	1.000	0.981	0.928	0.905	1.000	0.800	0.790	1.000	0.765	0.731	0.750	0.917	0.754	0.884	0.925	0.949	0.962	0.766	0.948	1.000	0.925	1.000
2049	0.811	0.868	1.000	0.977	1.000	0.923	0.934	1.000	0.995	0.859	1.000	0.983	0.888	0.963	1.000	0.920	0.832	0.928	0.978	0.916	0.861	1.000	1.000	1.000	1.000
2050	0.849	0.833	1.000	0.908	0.871	0.887	0.891	0.963	0.780	0.834	1.000	0.833	0.764	0.819	0.824	0.811	0.836	0.901	0.935	0.897	0.925	0.914	1.000	0.923	1.000

Year	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
2010	1.000	0.988	1.000	1.000	0.978	1.000	0.994	1.000	1.000	1.000	1.000	1.000	0.993	0.992	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	1.000	1.000	1.000	0.981	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.991	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.966	1.000	1.000	0.955	1.000	0.963	1.000	1.000	0.965	1.000	1.000	0.993	1.000	1.000	1.000	1.000	1.000	1.000	0.945	1.000	1.000	1.000	0.982
2013	1.000	0.931	1.000	1.000	0.998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.975	1.000	1.000	1.000	1.000	1.000	1.000	0.913	1.000	1.000	1.000	1.000
2014	0.955	0.964	1.000	1.000	0.984	1.000	1.000	0.972	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	0.926	0.823	1.000	1.000	0.799	1.000	0.940	1.000	1.000	0.880	1.000	1.000	1.000	0.886	1.000	1.000	0.904	0.924	1.000	0.904	1.000	1.000	1.000	0.945
2016	1.000	0.765	1.000	1.000	0.859	1.000	0.852	1.000	1.000	1.000	1.000	1.000	0.955	0.767	1.000	1.000	1.000	0.885	1.000	0.915	1.000	1.000	1.000	1.000
2017	1.000	0.971	1.000	1.000	1.000	1.000	0.922	1.000	1.000	1.000	1.000	1.000	1.000	0.861	1.000	1.000	1.000	1.000	1.000	0.972	1.000	1.000	1.000	1.000
2018	0.925	0.904	1.000	1.000	0.821	1.000	0.940	1.000	1.000	0.861	1.000	1.000	0.976	0.864	1.000	1.000	0.917	0.999	1.000	0.838	1.000	1.000	1.000	0.961
2019	1.000	0.960	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.979	1.000	1.000	0.972	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.000	1.000	1.000	1.000	1.000	1.000	0.989	1.000	1.000	1.000	1.000	1.000	0.912	0.950	1.000	1.000	1.000	1.000	1.000	0.892	1.000	1.000	1.000	1.000
2021	1.000	0.830	1.000	1.000	0.842	1.000	0.940	1.000	1.000	1.000	1.000	1.000	0.962	0.934	1.000	1.000	1.000	0.882	1.000	0.869	1.000	1.000	1.000	0.978
2022	1.000	0.965	1.000	1.000	0.847	1.000	0.873	1.000	1.000	0.969	1.000	1.000	1.000	0.805	1.000	1.000	0.956	1.000	1.000	0.913	1.000	1.000	1.000	1.000
2023	1.000	1.000	0.906	1.000	0.800	0.961	0.944	1.000	0.963	1.000	1.000	0.949	0.892	0.935	1.000	1.000	0.995	1.000	1.000	0.909	1.000	1.000	1.000	1.000
2024	1.000	0.872	0.997	1.000	0.945	0.991	0.989	1.000	1.000	1.000	1.000	1.000	0.998	0.955	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2025	1.000	0.841	1.000	1.000	0.917	1.000	0.968	1.000	1.000	1.000	1.000	1.000	0.948	0.947	1.000	0.931	1.000	0.983	1.000	0.929	1.000	1.000	1.000	0.999
2026	0.993	0.778	1.000	1.000	0.862	1.000	0.969	1.000	1.000	1.000	1.000	1.000	0.953	0.920	1.000	0.990	0.989	0.914	1.000	0.989	1.000	1.000	1.000	1.000
2027	0.990	0.714	1.000	1.000	0.882	1.000	0.787	1.000	1.000	1.000	0.905	0.971	0.976	0.706	1.000	0.846	0.956	0.918	1.000	0.796	1.000	0.973	1.000	1.000
2028	1.000	0.890	0.973	1.000	0.808	0.968	0.862	1.000	1.000	0.876	1.000	0.942	0.941	0.849	1.000	0.825	0.770	1.000	1.000	0.826	1.000	0.940	1.000	1.000
2029	0.984	0.755	0.969	1.000	0.750	0.949	0.862	1.000	1.000	0.898	1.000	0.913	0.884	0.790	1.000	0.783	0.993	0.829	1.000	0.772	1.000	0.852	1.000	0.920
2030	1.000	0.953	0.914	1.000	0.757	0.932	0.876	1.000	0.990	0.867	1.000	0.907	0.963	0.889	1.000	0.990	0.836	0.999	1.000	0.846	1.000	0.909	1.000	1.000
2031	1.000	0.912	1.000	1.000	0.854	1.000	0.835	1.000	1.000	0.908	1.000	1.000	1.000	0.763	1.000	0.837	0.810	1.000	1.000	0.911	1.000	1.000	0.950	1.000
2032	0.957	0.908	0.918	1.000	0.893	0.918	0.929	0.996	0.961	1.000	1.000	0.904	0.893	0.904	1.000	0.831	1.000	1.000	1.000	0.899	1.000	0.906	1.000	1.000
2033	1.000	0.994	0.988	1.000	0.852	0.938	0.905	1.000	0.978	0.852	1.000	0.915	0.988	0.817	1.000	0.769	0.905	1.000	1.000	0.935	1.000	0.957	1.000	1.000
2034	1.000	0.819	0.983	1.000	0.939	0.977	0.973	1.000	1.000	1.000	1.000	1.000	1.000	0.894	1.000	0.970	1.000	0.912	1.000	1.000	1.000	1.000	0.965	0.928
2035	0.978	0.825	0.779	0.867	0.799	0.759	0.918	1.000	0.880	0.731	1.000	0.778	0.777	0.884	1.000	0.795	0.735	0.943	0.863	0.869	1.000	0.823	1.000	1.000
2036	0.903	0.813	1.000	1.000	0.824	1.000	0.881	1.000	0.863	0.858	1.000	0.870	0.942	0.833	1.000	0.802	0.906	0.897	1.000	0.878	1.000	0.833	1.000	0.989
2037	1.000	0.824	1.000	1.000	0.858	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.968	1.000	1.000	1.000	1.000	0.899	1.000	1.000	1.000	1.000	0.934	1.000
2038	1.000	0.874	1.000	1.000	0.890	1.000	1.000	0.972	1.000	0.966	1.000	0.961	1.000	1.000	1.000	0.896	1.000	0.953	1.000	0.957	1.000	0.900	0.921	1.000
2039	0.991	0.916	0.950	0.968	0.902	0.999	1.000	1.000	0.876	0.868	1.000	0.871	0.910	1.000	1.000	0.891	0.903	1.000	0.999	0.952	1.000	0.886	0.999	1.000
2040	0.971	0.737	0.893	0.921	0.765	0.879	0.836	1.000	0.844	0.944	1.000	0.852	0.869	0.809	1.000	0.761	0.966	0.839	0.901	0.854	1.000	0.807	1.000	1.000
2041	0.906	0.780	0.943	0.898	0.871	0.961	0.847	0.919	0.809	0.902	1.000	0.817	0.970	0.817	0.949	0.783	0.886	0.916	0.954	0.776	1.000	0.707	0.921	0.977
2042	0.969	0.905	1.000	0.908	0.860	0.943	0.878	1.000	0.846	1.000	1.000	0.844	0.911	0.878	1.000	0.837	0.934	0.866	0.994	0.795	1.000	0.766	0.913	0.968
2043	1.000	0.864	0.975	0.922	0.810	0.936	0.889	1.000	0.826	1.000	1.000	0.840	0.956	0.826	1.000	0.911	0.979	0.870	0.994	0.867	1.000	0.800	1.000	0.980
2044	0.971	0.752	0.884	1.000	0.804	0.936	0.846	0.997	0.851	0.813	1.000	1.000	0.923	0.815	1.000	0.813	0.806	0.796	0.913	0.887	1.000	0.883	0.839	0.956
2045	0.900	0.787	0.912	0.835	0.929	0.898	0.721	0.964	0.786	0.908	1.000	0.800	0.868	0.621	0.992	0.759	0.961	0.931	0.938	0.718	1.000	0.711	0.958	0.997
2046	0.886	0.801	0.899	0.867	0.843	0.860	0.861	0.937	0.802	0.789	1.000	0.830	0.961	0.811	0.938	0.851	0.819	0.889	0.908	0.863	1.000	0.852	0.714	0.951
2047	0.897	0.920	1.000	0.818	0.914	0.907	0.860	0.996	0.727	0.748	1.000	0.779	0.936	0.748	1.000	0.677	0.814	0.925	0.963	0.816	1.000	0.733	0.730	1.000
2048	0.957	1.000	0.942	0.868	0.860	0.927	0.828	1.000	0.758	0.823	1.000	0.805	0.953	0.713	1.000	0.810	0.932	0.992	0.961	0.850	1.000	0.772	0.797	1.000
2049	1.000	0.969	0.903	0.898	0.875	0.845	0.929	1.000	0.832	0.893	1.000	0.833	0.903	0.882	1.000	0.806	0.874	0.982	0.899	0.917	1.000	0.857	0.881	1.000
2050	0.942	0.908	0.873	0.870	0.779	0.897	0.841	1.000	0.803	0.747	1.000	0.865	0.889	0.740	1.000	0.806	0.797	0.922	0.892	0.858	1.000	0.847	0.880	0.974

Figure 3-17. Water availability (municipal, industrial, themoelectric – 10% exceedance probability).

Year	AL	AZ	AR	CA	CO	CT	DE	DC	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
2010	1.000	0.939	1.000	1.000	1.000	0.975	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	0.953	1.000	0.979	1.000	1.000	1.000	1.000	1.000	0.991	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.886	1.000	0.987	0.986	0.984	0.965	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.987	1.000	1.000	1.000	1.000	0.987	1.000	1.000	1.000	1.000	1.000
2013	1.000	1.000	1.000	0.837	1.000	0.929	0.910	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.973	1.000	1.000	1.000	1.000	1.000
2014	1.000	1.000	1.000	0.896	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.919	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	1.000	0.614	1.000	0.696	0.752	1.000	0.976	1.000	1.000	0.902	1.000	1.000	1.000	1.000	0.791	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2016	1.000	0.511	1.000	0.583	1.000	0.887	0.957	1.000	0.888	0.742	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.998	1.000	1.000	1.000	1.000	1.000
2017	1.000	0.851	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.959	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2018	1.000	0.588	1.000	0.761	0.928	0.929	0.933	1.000	0.819	0.841	1.000	1.000	1.000	1.000	0.801	1.000	1.000	1.000	1.000	0.901	1.000	1.000	1.000	1.000	1.000
2019	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.000	1.000	1.000	0.995	1.000	0.873	0.954	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.899	1.000	1.000	1.000	1.000	1.000
2021	1.000	0.514	1.000	0.627	0.969	0.854	0.827	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.884	1.000	1.000	1.000	1.000	1.000
2022	1.000	0.836	1.000	0.923	0.993	1.000	1.000	1.000	0.862	0.826	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.943	1.000	1.000	1.000	1.000	1.000
2023	1.000	0.507	1.000	1.000	1.000	0.729	0.908	1.000	1.000	0.967	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.643	1.000	1.000	1.000	1.000	1.000
2024	1.000	0.924	1.000	0.794	1.000	0.925	1.000	1.000	0.795	0.915	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.774	1.000	1.000	1.000	1.000	1.000
2025	1.000	0.698	1.000	0.743	1.000	0.925	0.949	1.000	1.000	0.944	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.982	1.000	1.000	1.000	1.000	1.000
2026	1.000	0.546	1.000	0.544	1.000	0.807	0.932	1.000	1.000	0.906	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.830	1.000	1.000	1.000	1.000	1.000
2027	0.656	0.693	1.000	0.387	1.000	0.835	0.709	1.000	0.671	0.537	0.935	1.000	1.000	1.000	1.000	1.000	0.897	1.000	1.000	0.950	1.000	1.000	1.000	1.000	1.000
2028	0.774	0.790	1.000	0.786	1.000	0.776	0.782	1.000	1.000	0.745	1.000	1.000	1.000	1.000	0.995	1.000	0.895	1.000	1.000	0.794	1.000	1.000	1.000	1.000	1.000
2029	0.921	0.571	1.000	0.547	0.753	0.735	0.710	1.000	0.801	0.701	1.000	1.000	1.000	1.000	0.824	0.981	1.000	1.000	1.000	0.798	1.000	1.000	1.000	1.000	1.000
2030	1.000	0.656	1.000	0.889	0.862	0.722	0.781	1.000	1.000	0.977	1.000	1.000	0.938	0.993	1.000	1.000	1.000	1.000	1.000	0.784	1.000	1.000	1.000	1.000	1.000
2031	0.761	0.821	1.000	0.747	0.978	0.941	0.865	1.000	0.837	0.638	1.000	1.000	1.000	0.964	0.891	1.000	1.000	1.000	1.000	0.954	1.000	0.955	1.000	1.000	1.000
2032	0.974	0.851	1.000	0.875	1.000	0.779	0.895	1.000	1.000	0.879	1.000	0.983	0.811	0.915	1.000	1.000	1.000	1.000	1.000	0.795	1.000	0.976	1.000	1.000	1.000
2033	0.662	0.823	1.000	1.000	0.962	0.909	0.904	1.000	0.849	0.604	1.000	1.000	0.822	1.000	0.897	1.000	1.000	1.000	1.000	0.983	1.000	1.000	1.000	1.000	1.000
2034	0.857	0.775	1.000	0.715	1.000	1.000	1.000	1.000	0.798	0.772	1.000	1.000	1.000	0.964	1.000	1.000	1.000	1.000	1.000	0.989	0.846	1.000	1.000	1.000	1.000
2035	0.730	0.621	0.920	0.604	0.903	0.503	0.732	1.000	1.000	0.735	1.000	0.815	0.648	0.794	0.684	0.896	0.918	0.979	1.000	0.553	0.894	1.000	1.000	0.796	1.000
2036	0.731	0.549	1.000	0.548	0.762	0.921	0.797	1.000	0.793	0.668	1.000	0.886	0.630	0.627	0.720	0.849	1.000	1.000	1.000	1.000	1.000	0.961	1.000	1.000	1.000
2037	1.000	0.428	1.000	0.533	0.991	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.866	1.000	1.000	1.000	1.000	1.000	1.000	0.797	0.817	1.000	1.000	1.000
2038	0.702	0.538	1.000	0.662	1.000	1.000	1.000	1.000	0.903	0.859	1.000	1.000	0.939	0.801	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.751	1.000	1.000	1.000
2039	0.960	0.997	1.000	0.687	1.000	0.850	0.905	1.000	1.000	1.000	1.000	1.000	0.686	0.932	0.949	0.887	1.000	0.990	1.000	0.906	1.000	0.924	1.000	1.000	1.000
2040	0.573	0.346	1.000	0.418	0.785	0.704	0.759	1.000	0.982	0.700	1.000	1.000	0.679	0.975	0.968	0.843	1.000	0.950	1.000	0.761	0.928	1.000	1.000	1.000	1.000
2041	0.666	0.643	1.000	0.509	0.865	0.781	0.688	0.920	0.850	0.753	1.000	0.895	0.622	0.678	0.835	0.592	0.853	1.000	0.910	0.900	0.883	0.707	1.000	1.000	1.000
2042	0.672	0.478	1.000	0.976	0.924	0.839	0.672	0.865	0.782	0.816	1.000	1.000	0.727	0.745	1.000	0.908	0.894	1.000	0.898	0.987	0.756	0.923	1.000	1.000	1.000
2043	0.909	0.537	1.000	0.705	0.771	0.935	0.826	1.000	0.695	0.770	1.000	1.000	0.815	0.954	1.000	0.819	1.000	1.000	1.000	0.941	0.981	1.000	1.000	1.000	1.000
2044	0.679	0.286	1.000	0.478	0.826	0.837	0.885	1.000	0.964	0.799	1.000	0.672	0.474	0.607	0.903	0.733	0.822	0.787	1.000	0.782	0.632	0.857	1.000	0.893	1.000
2045	0.316	0.829	1.000	0.497	0.996	0.669	0.541	0.684	0.464	0.376	1.000	0.875	0.582	0.658	0.727	0.633	0.803	0.874	0.741	0.779	0.912	0.866	1.000	1.000	1.000
2046	0.577	0.728	1.000	0.635	0.864	0.771	0.741	1.000	0.477	0.690	1.000	0.552	0.387	0.328	0.726	0.712	0.687	1.000	0.930	0.760	0.347	0.502	1.000	0.856	1.000
2047	0.406	0.779	0.949	0.799	0.888	0.748	0.685	0.997	0.730	0.579	1.000	0.490	0.234	0.394	0.665	0.254	0.604	1.000	0.860	1.000	0.535	0.549	0.885	0.716	1.000
2048	0.512	0.962	1.000	1.000	0.961	0.828	0.742	1.000	0.599	0.521	1.000	0.530	0.326	0.473	0.833	0.509	0.768	0.848	0.897	0.887	0.487	0.896	1.000	0.850	1.000
2049	0.528	0.691	1.000	0.953	1.000	0.812	0.817	1.000	0.990	0.675	1.000	0.965	0.711	0.921	1.000	0.839	0.663	0.853	0.956	0.744	0.690	1.000	1.000	1.000	1.000
2050	0.613	0.605	1.000	0.808	0.742	0.724	0.691	0.926	0.557	0.614	1.000	0.665	0.370	0.606	0.648	0.614	0.672	0.797	0.869	0.676	0.828	0.828	1.000	0.846	1.000

Year	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
2010	1.000	0.976	1.000	1.000	0.955	1.000	0.988	1.000	1.000	1.000	1.000	1.000	0.985	0.985	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	1.000	1.000	1.000	0.962	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.982	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.931	1.000	1.000	0.909	1.000	0.925	1.000	1.000	0.929	1.000	1.000	0.985	1.000	1.000	1.000	1.000	1.000	1.000	0.889	1.000	1.000	1.000	0.964
2013	1.000	0.858	1.000	1.000	0.995	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.949	1.000	1.000	1.000	1.000	1.000	1.000	0.826	1.000	1.000	1.000	1.000
2014	0.909	0.926	1.000	1.000	0.969	1.000	1.000	0.944	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	0.853	0.636	1.000	1.000	0.597	1.000	0.879	1.000	1.000	0.760	1.000	1.000	1.000	0.772	1.000	1.000	0.808	0.848	1.000	0.808	1.000	1.000	1.000	0.890
2016	1.000	0.516	1.000	1.000	0.717	1.000	0.704	1.000	1.000	1.000	1.000	1.000	0.909	0.534	1.000	1.000	1.000	0.770	1.000	0.829	1.000	1.000	1.000	1.000
2017	1.000	0.940	1.000	1.000	1.000	1.000	0.845	1.000	1.000	1.000	1.000	1.000	1.000	0.721	1.000	1.000	1.000	1.000	1.000	0.945	1.000	1.000	1.000	1.000
2018	0.851	0.800	1.000	1.000	0.641	1.000	0.880	1.000	1.000	0.723	1.000	1.000	0.952	0.729	1.000	1.000	0.834	0.997	1.000	0.677	1.000	1.000	1.000	0.922
2019	1.000	0.917	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.957	1.000	1.000	0.943	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.000	1.000	1.000	1.000	1.000	1.000	0.978	1.000	1.000	1.000	1.000	1.000	0.825	0.898	1.000	1.000	1.000	1.000	1.000	0.780	1.000	1.000	1.000	1.000
2021	1.000	0.644	1.000	1.000	0.682	1.000	0.881	1.000	1.000	1.000	1.000	1.000	0.925	0.863	1.000	1.000	1.000	0.765	1.000	0.728	1.000	1.000	1.000	0.956
2022	1.000	0.927	1.000	1.000	0.690	1.000	0.747	1.000	1.000	0.937	1.000	1.000	1.000	0.588	1.000	1.000	0.912	1.000	1.000	0.817	1.000	1.000	1.000	1.000
2023	1.000	1.000	0.811	1.000	0.596	0.921	0.887	1.000	0.926	1.000	1.000	0.898	0.784	0.859	1.000	1.000	0.989	1.000	1.000	0.804	1.000	1.000	1.000	1.000
2024	1.000	0.730	0.994	1.000	0.889	0.982	0.977	1.000	1.000	1.000	1.000	1.000	0.996	0.900	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2025	1.000	0.662	1.000	1.000	0.831	1.000	0.935	1.000	1.000	1.000	1.000	1.000	0.897	0.880	1.000	0.863	1.000	0.966	1.000	0.839	1.000	1.000	1.000	0.998
2026	0.986	0.526	1.000	1.000	0.721	1.000	0.935	1.000	1.000	1.000	1.000	1.000	0.905	0.815	1.000	0.980	0.978	0.828	1.000	0.975	1.000	1.000	1.000	1.000
2027	0.980	0.388	1.000	1.000	0.760	1.000	0.552	1.000	1.000	1.000	0.811	0.941	0.953	0.299	1.000	0.691	0.912	0.836	1.000	0.518	1.000	0.946	1.000	1.000
2028	1.000	0.764	0.945	1.000	0.610	0.937	0.706	1.000	1.000	0.751	1.000	0.885	0.882	0.629	1.000	0.650	0.540	1.000	1.000	0.579	1.000	0.880	1.000	1.000
2029	0.967	0.472	0.938	1.000	0.493	0.898	0.701	1.000	1.000	0.796	1.000	0.827	0.768	0.469	1.000	0.557	0.987	0.657	1.000	0.433	1.000	0.704	1.000	0.841
2030	1.000	0.898	0.829	1.000	0.506	0.865	0.728	1.000	0.980	0.734	1.000	0.815	0.926	0.709	1.000	0.978	0.672	0.999	1.000	0.608	1.000	0.818	1.000	1.000
2031	1.000	0.809	1.000	1.000	0.702	1.000	0.632	1.000	1.000	0.815	1.000	1.000	1.000	0.356	1.000	0.649	0.620	1.000	1.000	0.768	1.000	1.000	0.901	1.000
2032	0.914	0.800	0.836	1.000	0.781	0.836	0.838	0.992	0.921	1.000	1.000	0.807	0.786	0.729	1.000	0.625	1.000	1.000	1.000	0.725	1.000	0.812	1.000	1.000
2033	1.000	0.988	0.976	1.000	0.697	0.877	0.780	1.000	0.956	0.705	1.000	0.829	0.976	0.461	1.000	0.470	0.810	1.000	1.000	0.818	1.000	0.915	1.000	1.000
2034	1.000	0.602	0.966	1.000	0.875	0.954	0.937	1.000	1.000	1.000	1.000	1.000	1.000	0.673	1.000	0.930	1.000	0.823	1.000	1.000	1.000	1.000	0.929	0.857
2035	0.957	0.614	0.544	0.735	0.589	0.508	0.803	1.000	0.759	0.462	1.000	0.538	0.544	0.622	1.000	0.494	0.471	0.886	0.726	0.608	1.000	0.647	1.000	1.000
2036	0.806	0.584	1.000	1.000	0.640	1.000	0.708	1.000	0.726	0.715	1.000	0.722	0.880	0.427	1.000	0.492	0.811	0.795	1.000	0.621	1.000	0.660	1.000	0.978
2037	1.000	0.608	1.000	1.000	0.709	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.933	1.000	1.000	1.000	1.000	0.799	1.000	1.000	1.000	1.000	0.868	1.000
2038	1.000	0.718	1.000	1.000	0.774	1.000	1.000	0.944	1.000	0.932	1.000	0.913	1.000	1.000	1.000	0.708	1.000	0.906	1.000	0.854	1.000	0.785	0.843	1.000
2039	0.982	0.811	0.888	0.935	0.798	0.998	1.000	1.000	0.752	0.736	1.000	0.704	0.809	1.000	1.000	0.677	0.806	1.000	0.999	0.830	1.000	0.747	0.998	1.000
2040	0.941	0.405	0.754	0.842	0.517	0.726	0.558	1.000	0.688	0.887	1.000	0.651	0.721	0.140	1.000	0.254	0.932	0.679	0.801	0.461	1.000	0.559	1.000	1.000
2041	0.812	0.499	0.865	0.797	0.735	0.910	0.575	0.837	0.619	0.804	1.000	0.557	0.934	0.105	0.897	0.282	0.771	0.832	0.906	0.136	1.000	0.307	0.843	0.955
2042	0.938	0.782	1.000	0.816	0.712	0.867	0.651	1.000	0.691	1.000	1.000	0.611	0.805	0.342	1.000	0.425	0.868	0.732	0.987	0.172	1.000	0.427	0.825	0.937
2043	1.000	0.688	0.938	0.844	0.607	0.846	0.675	1.000	0.645	1.000	1.000	0.589	0.903	0.000	1.000	0.665	0.958	0.741	0.987	0.432	1.000	0.493	1.000	0.960
2044	0.941	0.428	0.703	1.000	0.595	0.842	0.534	0.994	0.689	0.625	1.000	1.000	0.828	0.000	1.000	0.236	0.613	0.593	0.815	0.492	1.000	0.691	0.677	0.912
2045	0.800	0.505	0.769	0.669	0.854	0.742	0.128	0.929	0.546	0.816	1.000	0.454	0.703	0.000	0.984	0.000	0.921	0.863	0.867	0.000	1.000	0.204	0.916	0.994
2046	0.772	0.535	0.726	0.733	0.675	0.637	0.551	0.873	0.572	0.578	1.000	0.522	0.912	0.000	0.877	0.273	0.639	0.779	0.799	0.313	1.000	0.574	0.428	0.902
2047	0.794	0.811	1.000	0.630	0.822	0.753	0.532	0.991	0.398	0.496	1.000	0.355	0.854	0.000	1.000	0.000	0.627	0.849	0.917	0.015	1.000	0.196	0.461	1.000
2048	0.914	1.000	0.830	0.731	0.710	0.802	0.400	1.000	0.454	0.647	1.000	0.412	0.891	0.000	1.000	0.000	0.864	0.984	0.912	0.142	1.000	0.277	0.594	1.000
2049	1.000	0.927	0.704	0.789	0.739	0.564	0.743	1.000	0.612	0.785	1.000	0.476	0.773	0.000	1.000	0.000	0.747	0.965	0.767	0.491	1.000	0.522	0.761	1.000
2050	0.883	0.780	0.598	0.728	0.539	0.702	0.398	1.000	0.536	0.495	1.000	0.560	0.736	0.000	1.000	0.000	0.594	0.844	0.746	0.065	1.000	0.455	0.754	0.948

Figure 3-18. Water availability (mining – 10% exceedance probability).

Year	AL	AZ	AR	CA	CO	CT	DE	DC	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
2010	1.000	0.962	1.000	0.993	1.000	0.974	0.989	1.000	1.000	0.989	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.990	1.000	1.000	1.000	1.000	1.000
2011	1.000	0.959	1.000	0.971	0.994	0.988	1.000	1.000	1.000	0.973	1.000	1.000	1.000	1.000	0.986	1.000	1.000	1.000	1.000	0.981	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.919	1.000	0.965	0.964	0.948	0.949	1.000	1.000	0.992	1.000	1.000	1.000	1.000	0.964	1.000	1.000	1.000	1.000	0.954	1.000	1.000	1.000	1.000	1.000
2013	1.000	0.989	1.000	0.887	1.000	0.908	0.912	0.998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.935	1.000	1.000	1.000	1.000	1.000
2014	1.000	1.000	1.000	0.904	1.000	0.994	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.913	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	0.973	0.778	0.958	0.814	0.839	0.952	0.929	1.000	1.000	0.898	1.000	1.000	1.000	1.000	0.856	1.000	0.981	1.000	1.000	0.971	1.000	1.000	0.987	1.000	1.000
2016	0.990	0.732	1.000	0.763	0.993	0.873	0.921	1.000	0.896	0.825	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.932	1.000	1.000	1.000	1.000	1.000
2017	1.000	0.883	1.000	1.000	1.000	0.981	0.968	1.000	1.000	0.923	1.000	1.000	1.000	1.000	1.000	1.000	0.994	1.000	1.000	0.984	1.000	1.000	1.000	1.000	1.000
2018	0.996	0.768	1.000	0.844	0.918	0.892	0.909	1.000	0.865	0.869	1.000	1.000	0.999	0.975	0.860	1.000	1.000	1.000	1.000	0.887	1.000	1.000	1.000	1.000	1.000
2019	1.000	0.994	1.000	0.952	1.000	0.944	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.945	1.000	1.000	1.000	1.000	1.000
2020	1.000	1.000	1.000	0.949	1.000	0.866	0.918	1.000	1.000	0.943	1.000	1.000	1.000	1.000	0.991	1.000	1.000	1.000	1.000	0.886	1.000	1.000	1.000	1.000	1.000
2021	1.000	0.737	1.000	0.784	0.937	0.857	0.861	1.000	1.000	0.971	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.879	1.000	1.000	1.000	1.000	1.000
2022	0.952	0.878	1.000	0.916	0.948	0.926	0.948	1.000	0.883	0.862	1.000	1.000	1.000	1.000	0.962	1.000	0.972	1.000	1.000	0.906	1.000	1.000	1.000	1.000	1.000
2023	0.997	0.734	1.000	1.000	0.978	0.800	0.897	1.000	0.988	0.925	1.000	1.000	0.935	1.000	1.000	1.000	1.000	0.955	1.000	0.770	0.981	1.000	1.000	1.000	1.000
2024	1.000	0.916	1.000	0.859	1.000	0.889	0.964	1.000	0.853	0.902	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.829	1.000	1.000	1.000	1.000	1.000
2025	0.965	0.819	1.000	0.836	1.000	0.888	0.914	1.000	0.984	0.915	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.923	1.000	1.000	1.000	1.000	1.000
2026	0.971	0.753	1.000	0.747	0.988	0.835	0.907	1.000	0.949	0.897	1.000	1.000	1.000	0.977	0.962	1.000	0.977	1.000	1.000	0.856	1.000	0.971	1.000	1.000	1.000
2027	0.774	0.818	1.000	0.677	0.966	0.848	0.806	0.934	0.797	0.730	0.922	1.000	0.980	1.000	0.992	1.000	0.889	1.000	0.979	0.909	1.000	1.000	1.000	1.000	1.000
2028	0.827	0.859	1.000	0.855	0.987	0.822	0.840	1.000	0.954	0.824	1.000	1.000	1.000	1.000	0.947	1.000	0.888	1.000	1.000	0.842	0.984	1.000	0.980	1.000	1.000
2029	0.893	0.766	1.000	0.749	0.839	0.805	0.809	0.942	0.855	0.804	0.984	1.000	0.961	0.995	0.870	0.906	0.993	1.000	0.968	0.845	1.000	0.997	1.000	1.000	1.000
2030	1.000	0.803	1.000	0.902	0.889	0.800	0.842	1.000	0.964	0.928	1.000	0.992	0.894	0.926	0.965	1.000	1.000	0.987	1.000	0.840	1.000	1.000	1.000	1.000	1.000
2031	0.820	0.874	1.000	0.838	0.941	0.897	0.879	1.000	0.871	0.775	1.000	1.000	1.000	0.913	0.900	1.000	0.947	1.000	1.000	0.912	0.978	0.913	1.000	1.000	1.000
2032	0.916	0.887	1.000	0.895	0.979	0.828	0.892	1.000	1.000	0.883	1.000	0.915	0.835	0.890	0.951	0.965	0.957	1.000	1.000	0.847	0.929	0.923	1.000	1.000	1.000
2033	0.775	0.875	0.960	0.984	0.934	0.884	0.897	1.000	0.876	0.759	1.000	0.966	0.840	0.968	0.903	0.967	0.937	1.000	1.000	0.924	0.978	1.000	0.959	0.987	1.000
2034	0.862	0.856	1.000	0.824	0.964	0.949	0.998	1.000	0.853	0.836	1.000	1.000	0.945	0.911	1.000	1.000	1.000	1.000	1.000	0.926	0.855	0.943	1.000	1.000	1.000
2035	0.805	0.791	0.915	0.776	0.907	0.715	0.827	0.979	0.978	0.820	1.000	0.839	0.761	0.835	0.807	0.867	0.897	0.925	0.941	0.756	0.877	0.935	1.000	0.850	1.000
2036	0.805	0.762	1.000	0.751	0.843	0.890	0.855	0.964	0.850	0.792	1.000	0.870	0.753	0.759	0.823	0.846	0.965	1.000	0.972	0.961	1.000	0.915	1.000	0.959	1.000
2037	1.000	0.713	1.000	0.744	0.947	0.935	1.000	1.000	0.954	1.000	1.000	1.000	0.978	0.867	1.000	1.000	1.000	1.000	1.000	0.947	0.832	0.850	1.000	1.000	1.000
2038	0.791	0.759	1.000	0.802	0.985	0.930	0.959	1.000	0.900	0.877	1.000	1.000	0.892	0.837	0.964	0.921	1.000	1.000	1.000	0.963	0.968	0.820	1.000	1.000	1.000
2039	0.908	0.949	1.000	0.813	1.000	0.862	0.900	1.000	1.000	1.000	1.000	0.947	0.779	0.896	0.926	0.863	0.994	0.929	1.000	0.896	0.937	0.898	1.000	1.000	1.000
2040	0.738	0.683	1.000	0.695	0.854	0.805	0.845	0.934	0.936	0.810	1.000	0.962	0.779	0.915	0.935	0.843	0.996	0.910	0.931	0.845	0.891	0.939	0.979	1.000	1.000
2041	0.782	0.805	1.000	0.735	0.890	0.836	0.819	0.889	0.876	0.834	1.000	0.874	0.758	0.780	0.875	0.729	0.866	0.966	0.887	0.895	0.870	0.799	1.000	0.961	1.000
2042	0.787	0.740	1.000	0.940	0.917	0.859	0.815	0.864	0.845	0.861	1.000	0.940	0.805	0.811	1.000	0.872	0.885	0.972	0.881	0.926	0.812	0.897	1.000	1.000	1.000
2043	0.888	0.764	1.000	0.822	0.847	0.897	0.873	0.995	0.805	0.842	1.000	1.000	0.844	0.904	0.980	0.831	1.000	0.959	0.944	0.911	0.914	1.000	1.000	1.000	1.000
2044	0.795	0.666	0.989	0.723	0.872	0.859	0.896	0.944	0.927	0.855	1.000	0.773	0.709	0.748	0.905	0.792	0.851	0.836	0.982	0.858	0.758	0.866	1.000	0.893	1.000
2045	0.654	0.883	1.000	0.731	0.949	0.796	0.775	0.781	0.701	0.684	1.000	0.864	0.756	0.772	0.826	0.747	0.843	0.875	0.810	0.859	0.884	0.870	0.990	0.960	1.000
2046	0.761	0.843	1.000	0.792	0.889	0.835	0.847	0.935	0.707	0.813	1.000	0.718	0.686	0.628	0.825	0.783	0.790	0.933	0.895	0.854	0.642	0.705	0.955	0.876	1.000
2047	0.700	0.864	0.928	0.864	0.900	0.827	0.830	0.923	0.821	0.769	1.000	0.690	0.635	0.662	0.798	0.575	0.752	0.939	0.863	0.937	0.726	0.727	0.894	0.812	1.000
2048	0.744	0.936	0.966	1.000	0.933	0.858	0.851	0.936	0.762	0.748	1.000	0.708	0.677	0.699	0.873	0.690	0.826	0.863	0.880	0.897	0.710	0.883	0.964	0.873	1.000
2049	0.755	0.831	0.987	0.931	0.993	0.852	0.877	0.970	0.938	0.810	1.000	0.905	0.819	0.892	0.999	0.840	0.779	0.866	0.907	0.855	0.797	0.934	0.953	1.000	1.000
2050	0.789	0.800	0.956	0.868	0.834	0.820	0.839	0.891	0.744	0.787	1.000	0.769	0.706	0.762	0.790	0.742	0.782	0.842	0.867	0.837	0.854	0.852	0.992	0.870	1.000

Year	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
2010	1.000	0.979	1.000	1.000	0.970	1.000	0.982	1.000	1.000	1.000	1.000	1.000	0.979	0.976	1.000	1.000	0.999	0.994	1.000	0.987	1.000	1.000	1.000	1.000
2011	1.000	0.982	1.000	1.000	0.963	1.000	0.992	1.000	1.000	0.981	1.000	1.000	1.000	0.959	1.000	1.000	0.989	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	0.976	0.938	1.000	1.000	0.929	1.000	0.927	1.000	1.000	0.935	1.000	1.000	0.949	0.951	1.000	1.000	1.000	0.983	1.000	0.904	1.000	1.000	1.000	0.955
2013	1.000	0.896	1.000	1.000	0.958	1.000	0.948	1.000	1.000	1.000	1.000	1.000	0.918	0.972	1.000	1.000	1.000	1.000	1.000	0.860	1.000	1.000	1.000	1.000
2014	0.910	0.916	1.000	1.000	0.936	1.000	0.999	0.920	1.000	0.964	1.000	1.000	1.000	0.984	0.989	1.000	0.984	1.000	1.000	0.977	1.000	1.000	1.000	0.996
2015	0.885	0.788	1.000	1.000	0.769	1.000	0.879	1.000	1.000	0.837	1.000	1.000	0.985	0.813	1.000	0.926	0.861	0.880	1.000	0.835	1.000	1.000	1.000	0.902
2016	1.000	0.736	1.000	1.000	0.823	1.000	0.800	1.000	1.000	1.000	1.000	1.000	0.885	0.705	1.000	1.000	1.000	0.845	1.000	0.845	1.000	1.000	1.000	1.000
2017	1.000	0.923	1.000	1.000	0.976	1.000	0.863	1.000	1.000	0.949	1.000	1.000	0.947	0.789	1.000	1.000	0.954	0.964	1.000	0.896	1.000	1.000	1.000	1.000
2018	0.884	0.862	1.000	1.000	0.789	1.000	0.879	1.000	1.000	0.820	1.000	1.000	0.904	0.793	0.960	0.926	0.872	0.947	1.000	0.775	1.000	1.000	1.000	0.916
2019	1.000	0.913	1.000	1.000	0.968	1.000	1.000	1.000	1.000	0.926	1.000	1.000	0.900	0.996	1.000	1.000	0.970	1.000	1.000	0.973	1.000	1.000	1.000	1.000
2020	0.955	0.990	1.000	1.000	0.959	1.000	0.922	1.000	1.000	1.000	1.000	1.000	0.847	0.870	1.000	1.000	1.000	1.000	1.000	0.823	1.000	1.000	1.000	1.000
2021	1.000	0.795	1.000	0.983	0.808	1.000	0.878	1.000	1.000	1.000	1.000	0.934	0.892	0.855	1.000	1.000	0.998	0.842	1.000	0.803	1.000	1.000	1.000	0.932
2022	1.000	0.917	1.000	1.000	0.812	1.000	0.817	1.000	1.000	0.916	1.000	1.000	0.942	0.739	1.000	0.940	0.907	1.000	1.000	0.843	1.000	1.000	1.000	1.000
2023	1.000	0.986	0.832	0.967	0.769	0.880	0.881	1.000	0.881	1.000	1.000	0.867	0.828	0.856	1.000	0.954	0.942	0.999	0.945	0.839	1.000	0.987	1.000	1.000
2024	1.000	0.834	0.915	1.000	0.901	0.907	0.921	1.000	1.000	1.000	0.976	1.000	0.924	0.874	1.000	1.000	1.000	0.994	0.970	0.950	0.966	1.000	1.000	1.000
2025	1.000	0.805	1.000	1.000	0.875	1.000	0.903	1.000	1.000	1.000	1.000	1.000	0.879	0.867	1.000	0.857	1.000	0.933	1.000	0.857	1.000	1.000	1.000	0.951
2026	0.945	0.748	0.939	1.000	0.826	0.951	0.903	1.000	1.000	0.969	1.000	0.987	0.883	0.843	1.000	0.910	0.936	0.871	1.000	0.911	1.000	1.000	0.976	1.000
2027	0.942	0.691	1.000	0.983	0.843	0.999	0.739	1.000	0.979	0.954	0.866	0.886	0.904	0.649	1.000	0.779	0.906	0.874	1.000	0.737	0.988	0.881	0.994	0.957
2028	0.984	0.850	0.892	0.975	0.777	0.886	0.807	1.000	0.990	0.832	1.000	0.861	0.872	0.779	1.000	0.760	0.738	1.000	0.988	0.764	1.000	0.851	0.978	1.000
2029	0.937	0.728	0.889	0.933	0.725	0.868	0.807	0.984	0.964	0.852	0.994	0.834	0.820	0.725	1.000	0.722	0.940	0.793	0.982	0.715	1.000	0.772	1.000	0.880
2030	0.958	0.907	0.839	0.932	0.731	0.853	0.820	1.000	0.906	0.824	1.000	0.829	0.892	0.815	1.000	0.909	0.798	0.947	0.926	0.782	1.000	0.823	1.000	0.996
2031	0.996	0.870	0.923	1.000	0.818	0.950	0.783	1.000	1.000	0.860	1.000	0.923	0.934	0.701	1.000	0.771	0.774	0.955	1.000	0.841	1.000	0.948	0.884	1.000
2032	0.912	0.866	0.842	0.961	0.853	0.840	0.867	0.939	0.879	0.946	1.000	0.825	0.828	0.828	1.000	0.765	0.959	0.949	0.932	0.830	1.000	0.820	0.958	0.963
2033	0.952	0.944	0.905	0.981	0.816	0.858	0.846	1.000	0.895	0.810	1.000	0.835	0.914	0.750	1.000	0.709	0.860	0.973	0.980	0.863	1.000	0.867	1.000	1.000
2034	0.954	0.786	0.901	1.000	0.895	0.893	0.908	1.000	1.000	0.994	1.000	0.955	0.930	0.819	1.000	0.891	1.000	0.868	0.987	1.000	1.000	1.000	0.896	0.887
2035	0.932	0.791	0.716	0.800	0.768	0.696	0.858	1.000	0.806	0.700	1.000	0.712	0.724	0.810	1.000	0.733	0.706	0.896	0.799	0.804	1.000	0.746	0.936	0.973
2036	0.864	0.780	0.968	0.925	0.791	0.952	0.824	1.000	0.791	0.815	0.974	0.795	0.873	0.764	1.000	0.739	0.860	0.855	1.000	0.812	1.000	0.755	0.951	0.942
2037	0.972	0.790	0.945	1.000	0.822	0.921	1.000	0.971	0.983	1.000	1.000	0.972	0.896	1.000	0.969	1.000	0.987	0.857	1.000	0.989	1.000	0.960	0.867	0.964
2038	0.977	0.836	0.949	0.969	0.851	0.938	0.947	0.916	0.946	0.913	1.000	0.878	0.947	0.929	0.970	0.824	1.000	0.905	0.990	0.882	1.000	0.815	0.856	1.000
2039	0.943	0.874	0.871	0.890	0.862	0.913	0.949	0.987	0.802	0.824	1.000	0.796	0.844	0.998	0.986	0.819	0.858	1.000	0.921	0.878	1.000	0.802	0.926	1.000
2040	0.925	0.712	0.820	0.848	0.738	0.805	0.784	1.000	0.774	0.892	1.000	0.779	0.807	0.736	1.000	0.702	0.914	0.802	0.832	0.789	1.000	0.731	0.937	1.000
2041	0.866	0.751	0.865	0.827	0.834	0.879	0.793	0.867	0.742	0.854	1.000	0.748	0.898	0.742	0.902	0.722	0.842	0.871	0.880	0.712	1.000	0.641	0.855	0.931
2042	0.923	0.864	0.928	0.836	0.824	0.863	0.821	1.000	0.776	0.970	1.000	0.772	0.845	0.803	0.962	0.770	0.885	0.826	0.916	0.731	1.000	0.694	0.847	0.923
2043	0.953	0.827	0.894	0.849	0.778	0.856	0.832	1.000	0.758	0.950	1.000	0.769	0.886	0.746	1.000	0.838	0.926	0.830	0.917	0.801	1.000	0.725	0.976	0.933
2044	0.925	0.726	0.812	0.925	0.773	0.857	0.793	0.937	0.780	0.773	1.000	0.915	0.856	0.737	0.967	0.747	0.770	0.763	0.843	0.820	1.000	0.800	0.780	0.912
2045	0.861	0.757	0.838	0.769	0.887	0.822	0.680	0.907	0.722	0.859	0.970	0.733	0.806	0.561	0.941	0.686	0.909	0.885	0.866	0.649	1.000	0.644	0.887	0.949
2046	0.848	0.770	0.826	0.798	0.809	0.788	0.807	0.882	0.736	0.752	1.000	0.760	0.891	0.733	0.892	0.780	0.781	0.846	0.839	0.798	1.000	0.772	0.666	0.907
2047	0.858	0.877	0.947	0.754	0.873	0.831	0.806	0.935	0.669	0.714	1.000	0.714	0.869	0.676	0.948	0.612	0.776	0.878	0.888	0.738	1.000	0.664	0.681	0.985
2048	0.912	0.995	0.864	0.800	0.824	0.849	0.776	1.000	0.697	0.782	1.000	0.738	0.884	0.644	1.000	0.733	0.883	0.939	0.887	0.775	1.000	0.699	0.741	0.997
2049	1.000	0.922	0.829	0.827	0.838	0.775	0.868	1.000	0.764	0.845	1.000	0.763	0.839	0.797	1.000	0.729	0.830	0.930	0.831	0.847	1.000	0.777	0.817	1.000
2050	0.898	0.867	0.803	0.801	0.751	0.822	0.789	0.999	0.738	0.713	1.000	0.792	0.826	0.669	1.000	0.729	0.760	0.875	0.825	0.779	1.000	0.767	0.815	0.928

Figure 3-19. Water availability (municipal, industrial, themoelectric – 1% exceedance probability).

Year	AL	AZ	AR	CA	CO	CT	DE	DC	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
2010	1.000	0.924	1.000	0.987	1.000	0.947	0.978	1.000	1.000	0.977	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.981	1.000	1.000	1.000	1.000	1.000
2011	1.000	0.917	1.000	0.941	0.989	0.975	1.000	1.000	1.000	0.946	1.000	1.000	1.000	1.000	0.971	1.000	1.000	1.000	1.000	0.963	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.836	1.000	0.930	0.929	0.895	0.898	1.000	1.000	0.983	1.000	1.000	1.000	1.000	0.929	1.000	1.000	1.000	1.000	0.909	1.000	1.000	1.000	1.000	1.000
2013	1.000	0.977	1.000	0.774	1.000	0.815	0.824	0.997	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.870	1.000	1.000	1.000	1.000	1.000
2014	1.000	1.000	1.000	0.807	1.000	0.989	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.827	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	0.946	0.548	0.917	0.626	0.678	0.905	0.859	1.000	1.000	0.795	1.000	1.000	1.000	1.000	0.711	1.000	0.961	1.000	1.000	0.942	1.000	1.000	0.973	1.000	1.000
2016	0.980	0.455	1.000	0.524	0.986	0.746	0.842	1.000	0.792	0.650	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.864	1.000	1.000	1.000	1.000	1.000
2017	1.000	0.762	1.000	1.000	1.000	0.961	0.936	1.000	1.000	0.845	1.000	1.000	1.000	1.000	1.000	1.000	0.988	1.000	1.000	0.968	1.000	1.000	1.000	1.000	1.000
2018	0.992	0.524	1.000	0.685	0.837	0.783	0.818	1.000	0.729	0.738	1.000	1.000	0.997	0.950	0.721	1.000	1.000	1.000	1.000	0.775	1.000	1.000	1.000	1.000	1.000
2019	1.000	0.987	1.000	0.903	1.000	0.888	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.890	1.000	1.000	1.000	1.000	1.000
2020	1.000	1.000	1.000	0.897	1.000	0.732	0.836	1.000	1.000	0.885	1.000	1.000	1.000	1.000	0.981	1.000	1.000	1.000	1.000	0.772	1.000	1.000	1.000	1.000	1.000
2021	1.000	0.457	1.000	0.564	0.874	0.714	0.721	1.000	1.000	0.941	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.758	1.000	1.000	1.000	1.000	1.000
2022	0.903	0.748	1.000	0.831	0.896	0.852	0.896	1.000	0.767	0.723	1.000	1.000	1.000	1.000	0.924	1.000	0.945	1.000	1.000	0.811	1.000	1.000	1.000	1.000	1.000
2023	0.993	0.449	1.000	1.000	0.957	0.601	0.793	1.000	0.975	0.850	1.000	1.000	0.869	1.000	1.000	1.000	1.000	0.911	1.000	0.539	0.961	1.000	1.000	1.000	1.000
2024	1.000	0.826	1.000	0.714	1.000	0.778	0.927	1.000	0.706	0.803	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.657	1.000	1.000	1.000	1.000	1.000
2025	0.929	0.622	1.000	0.668	1.000	0.777	0.829	1.000	0.968	0.829	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.844	1.000	1.000	1.000	1.000	1.000
2026	0.942	0.484	1.000	0.488	0.976	0.671	0.813	1.000	0.899	0.794	1.000	1.000	1.000	0.953	0.924	1.000	0.953	1.000	1.000	0.705	1.000	0.943	1.000	1.000	1.000
2027	0.549	0.617	1.000	0.346	0.932	0.695	0.611	0.869	0.593	0.460	0.845	1.000	0.961	0.999	0.983	1.000	0.778	1.000	0.958	0.812	1.000	1.000	1.000	1.000	1.000
2028	0.654	0.704	1.000	0.707	0.973	0.641	0.676	1.000	0.908	0.648	1.000	1.000	1.000	1.000	0.895	1.000	0.776	1.000	1.000	0.669	0.967	1.000	0.960	1.000	1.000
2029	0.787	0.506	1.000	0.491	0.679	0.602	0.609	0.883	0.710	0.607	0.969	1.000	0.923	0.989	0.740	0.813	0.985	1.000	0.937	0.670	1.000	0.994	1.000	1.000	1.000
2030	1.000	0.582	1.000	0.800	0.777	0.588	0.672	1.000	0.928	0.856	1.000	0.985	0.787	0.852	0.930	1.000	1.000	0.974	1.000	0.656	1.000	1.000	1.000	1.000	1.000
2031	0.640	0.731	1.000	0.671	0.882	0.784	0.746	1.000	0.742	0.550	1.000	1.000	1.000	0.825	0.801	1.000	0.895	1.000	1.000	0.808	0.955	0.827	1.000	1.000	1.000
2032	0.832	0.758	1.000	0.787	0.958	0.637	0.773	1.000	1.000	0.767	1.000	0.830	0.671	0.780	0.902	0.929	0.914	1.000	1.000	0.662	0.857	0.845	1.000	1.000	1.000
2033	0.550	0.732	0.919	0.967	0.868	0.753	0.779	1.000	0.753	0.518	1.000	0.932	0.680	0.937	0.806	0.935	0.873	1.000	1.000	0.829	0.955	1.000	0.919	0.975	1.000
2034	0.725	0.689	1.000	0.642	0.927	0.891	0.995	1.000	0.707	0.669	1.000	1.000	0.889	0.823	1.000	1.000	1.000	1.000	1.000	0.833	0.710	0.886	1.000	1.000	1.000
2035	0.610	0.549	0.830	0.542	0.814	0.382	0.621	0.958	0.957	0.634	1.000	0.677	0.522	0.669	0.614	0.734	0.795	0.849	0.882	0.436	0.754	0.870	1.000	0.701	1.000
2036	0.610	0.483	1.000	0.491	0.686	0.759	0.677	0.929	0.701	0.573	1.000	0.741	0.505	0.518	0.646	0.692	0.929	1.000	0.944	0.908	1.000	0.830	1.000	0.917	1.000
2037	1.000	0.374	1.000	0.477	0.894	0.856	1.000	1.000	0.909	1.000	1.000	1.000	0.956	0.733	1.000	1.000	1.000	1.000	1.000	0.873	0.664	0.699	1.000	1.000	1.000
2038	0.582	0.472	1.000	0.594	0.970	0.844	0.906	1.000	0.800	0.743	1.000	1.000	0.784	0.674	0.928	0.841	1.000	1.000	1.000	0.909	0.935	0.640	1.000	1.000	1.000
2039	0.813	0.887	1.000	0.617	1.000	0.690	0.768	1.000	1.000	1.000	1.000	0.894	0.553	0.792	0.852	0.726	0.989	0.857	1.000	0.744	0.874	0.795	1.000	1.000	1.000
2040	0.461	0.298	1.000	0.373	0.707	0.557	0.635	0.868	0.871	0.597	1.000	0.924	0.543	0.830	0.870	0.685	0.991	0.820	0.862	0.610	0.781	0.879	0.958	1.000	1.000
2041	0.542	0.566	1.000	0.455	0.779	0.624	0.568	0.777	0.751	0.644	1.000	0.747	0.488	0.560	0.749	0.458	0.733	0.933	0.774	0.732	0.739	0.598	1.000	0.921	1.000
2042	0.545	0.416	1.000	0.877	0.833	0.676	0.551	0.727	0.689	0.700	1.000	0.881	0.579	0.621	1.000	0.743	0.769	0.945	0.762	0.807	0.624	0.794	1.000	1.000	1.000
2043	0.756	0.469	1.000	0.632	0.694	0.761	0.688	0.990	0.610	0.657	1.000	1.000	0.655	0.809	0.961	0.663	1.000	0.918	0.888	0.762	0.827	1.000	1.000	1.000	1.000
2044	0.544	0.242	0.978	0.427	0.744	0.671	0.739	0.887	0.854	0.682	1.000	0.545	0.342	0.495	0.810	0.585	0.703	0.671	0.965	0.615	0.509	0.733	1.000	0.785	1.000
2045	0.213	0.732	1.000	0.444	0.897	0.518	0.425	0.563	0.402	0.299	1.000	0.729	0.436	0.539	0.651	0.494	0.685	0.750	0.620	0.608	0.760	0.741	0.979	0.920	1.000
2046	0.445	0.639	1.000	0.568	0.779	0.609	0.603	0.869	0.413	0.581	1.000	0.436	0.255	0.239	0.651	0.565	0.580	0.866	0.791	0.587	0.246	0.411	0.910	0.752	1.000
2047	0.287	0.685	0.856	0.717	0.800	0.587	0.549	0.845	0.641	0.479	1.000	0.380	0.111	0.297	0.595	0.151	0.505	0.878	0.727	0.817	0.413	0.454	0.789	0.624	1.000
2048	0.379	0.850	0.933	1.000	0.866	0.658	0.596	0.872	0.523	0.426	1.000	0.417	0.189	0.366	0.747	0.381	0.652	0.724	0.760	0.692	0.367	0.766	0.928	0.745	1.000
2049	0.389	0.604	0.974	0.855	0.985	0.642	0.661	0.940	0.876	0.564	1.000	0.810	0.531	0.768	0.998	0.678	0.557	0.727	0.813	0.558	0.546	0.868	0.905	1.000	1.000
2050	0.460	0.525	0.912	0.724	0.668	0.561	0.543	0.781	0.485	0.507	1.000	0.538	0.217	0.481	0.580	0.472	0.565	0.674	0.734	0.490	0.667	0.704	0.984	0.741	1.000

Year	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
2010	1.000	0.957	1.000	1.000	0.940	1.000	0.963	1.000	1.000	1.000	1.000	1.000	0.958	0.953	1.000	1.000	0.998	0.989	1.000	0.974	1.000	1.000	1.000	1.000
2011	1.000	0.963	1.000	1.000	0.926	1.000	0.983	1.000	1.000	0.962	1.000	1.000	1.000	0.917	1.000	1.000	0.978	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	0.951	0.874	1.000	1.000	0.858	1.000	0.854	1.000	1.000	0.871	1.000	1.000	0.899	0.902	1.000	1.000	1.000	0.966	1.000	0.807	1.000	1.000	1.000	0.909
2013	1.000	0.788	1.000	1.000	0.916	1.000	0.896	1.000	1.000	1.000	1.000	1.000	0.837	0.944	1.000	1.000	1.000	1.000	1.000	0.719	1.000	1.000	1.000	1.000
2014	0.821	0.828	1.000	1.000	0.872	1.000	0.998	0.839	1.000	0.929	1.000	1.000	1.000	0.968	0.979	1.000	0.967	1.000	1.000	0.953	1.000	1.000	1.000	0.992
2015	0.770	0.565	1.000	1.000	0.535	1.000	0.758	1.000	1.000	0.674	1.000	1.000	0.970	0.626	1.000	0.851	0.721	0.760	1.000	0.670	1.000	1.000	1.000	0.804
2016	1.000	0.457	1.000	1.000	0.644	1.000	0.600	1.000	1.000	1.000	1.000	1.000	0.771	0.410	1.000	1.000	1.000	0.689	1.000	0.689	1.000	1.000	1.000	1.000
2017	1.000	0.840	1.000	1.000	0.952	1.000	0.726	1.000	1.000	0.898	1.000	1.000	0.895	0.579	1.000	1.000	0.907	0.927	1.000	0.793	1.000	1.000	1.000	1.000
2018	0.768	0.713	1.000	1.000	0.575	1.000	0.757	1.000	1.000	0.640	1.000	1.000	0.809	0.585	0.921	0.852	0.744	0.895	1.000	0.550	1.000	1.000	1.000	0.833
2019	1.000	0.818	1.000	1.000	0.935	1.000	1.000	1.000	1.000	0.851	1.000	1.000	0.801	0.993	1.000	1.000	0.940	1.000	1.000	0.946	1.000	1.000	1.000	1.000
2020	0.909	0.979	1.000	1.000	0.916	1.000	0.845	1.000	1.000	1.000	1.000	1.000	0.694	0.735	1.000	1.000	1.000	1.000	1.000	0.640	1.000	1.000	1.000	1.000
2021	1.000	0.571	1.000	0.967	0.612	0.999	0.756	1.000	1.000	1.000	1.000	0.868	0.784	0.700	1.000	1.000	0.996	0.684	1.000	0.590	1.000	1.000	1.000	0.864
2022	1.000	0.826	1.000	1.000	0.620	1.000	0.635	1.000	1.000	0.833	1.000	1.000	0.885	0.448	1.000	0.880	0.814	1.000	1.000	0.668	1.000	1.000	1.000	1.000
2023	1.000	0.970	0.664	0.935	0.534	0.760	0.760	1.000	0.763	1.000	1.000	0.735	0.656	0.689	1.000	0.908	0.883	0.998	0.891	0.652	1.000	0.974	1.000	1.000
2024	1.000	0.648	0.829	1.000	0.799	0.814	0.840	1.000	1.000	1.000	0.952	1.000	0.848	0.722	1.000	1.000	1.000	0.988	0.939	0.891	0.932	1.000	1.000	1.000
2025	1.000	0.586	1.000	1.000	0.747	1.000	0.801	1.000	1.000	1.000	1.000	1.000	0.758	0.699	1.000	0.714	1.000	0.866	1.000	0.677	1.000	1.000	1.000	0.901
2026	0.890	0.462	0.878	1.000	0.647	0.901	0.799	1.000	1.000	0.939	1.000	0.974	0.765	0.635	1.000	0.820	0.872	0.741	1.000	0.796	1.000	1.000	0.951	1.000
2027	0.884	0.338	1.000	0.966	0.682	0.998	0.452	1.000	0.957	0.908	0.731	0.773	0.808	0.164	1.000	0.558	0.813	0.748	1.000	0.379	0.977	0.762	0.988	0.913
2028	0.967	0.677	0.784	0.951	0.547	0.772	0.588	1.000	0.981	0.663	1.000	0.722	0.744	0.456	1.000	0.519	0.476	1.000	0.976	0.429	1.000	0.702	0.955	1.000
2029	0.873	0.413	0.777	0.865	0.441	0.736	0.582	0.969	0.928	0.704	0.988	0.669	0.640	0.304	1.000	0.432	0.880	0.586	0.964	0.292	1.000	0.543	1.000	0.759
2030	0.916	0.798	0.678	0.864	0.453	0.706	0.605	1.000	0.812	0.648	1.000	0.658	0.783	0.514	1.000	0.809	0.595	0.895	0.852	0.445	1.000	0.647	1.000	0.991
2031	0.993	0.717	0.846	1.000	0.630	0.901	0.515	1.000	1.000	0.721	1.000	0.847	0.869	0.187	1.000	0.506	0.549	0.911	1.000	0.583	1.000	0.896	0.768	1.000
2032	0.825	0.708	0.684	0.923	0.701	0.680	0.698	0.877	0.758	0.892	1.000	0.651	0.657	0.515	1.000	0.479	0.918	0.897	0.864	0.539	1.000	0.641	0.917	0.927
2033	0.905	0.878	0.810	0.962	0.625	0.717	0.643	1.000	0.790	0.621	1.000	0.671	0.827	0.262	1.000	0.333	0.720	0.946	0.961	0.615	1.000	0.733	1.000	1.000
2034	0.907	0.529	0.799	1.000	0.786	0.786	0.783	1.000	1.000	0.988	1.000	0.909	0.858	0.442	1.000	0.741	1.000	0.736	0.975	1.000	1.000	1.000	0.792	0.774
2035	0.863	0.539	0.415	0.600	0.527	0.379	0.658	1.000	0.612	0.400	1.000	0.401	0.435	0.383	1.000	0.341	0.413	0.792	0.598	0.410	1.000	0.491	0.872	0.945
2036	0.727	0.512	0.932	0.851	0.573	0.900	0.569	1.000	0.582	0.629	0.948	0.563	0.737	0.191	1.000	0.330	0.720	0.709	1.000	0.413	1.000	0.499	0.901	0.883
2037	0.943	0.533	0.882	1.000	0.635	0.832	1.000	0.942	0.967	1.000	1.000	0.939	0.783	1.000	0.938	1.000	0.973	0.713	1.000	0.964	1.000	0.916	0.735	0.927
2038	0.953	0.632	0.889	0.938	0.694	0.866	0.865	0.831	0.891	0.825	1.000	0.727	0.888	0.725	0.939	0.505	1.000	0.810	0.980	0.603	1.000	0.602	0.712	1.000
2039	0.886	0.715	0.711	0.780	0.716	0.809	0.864	0.974	0.605	0.648	1.000	0.532	0.670	0.991	0.972	0.465	0.715	1.000	0.843	0.570	1.000	0.561	0.852	1.000
2040	0.849	0.348	0.585	0.696	0.462	0.559	0.417	1.000	0.547	0.784	1.000	0.479	0.588	0.000	1.000	0.070	0.829	0.604	0.664	0.225	1.000	0.385	0.874	1.000
2041	0.732	0.433	0.681	0.655	0.659	0.721	0.427	0.734	0.484	0.709	1.000	0.389	0.780	0.000	0.803	0.080	0.683	0.742	0.757	0.000	1.000	0.150	0.710	0.862
2042	0.846	0.688	0.825	0.671	0.638	0.678	0.491	1.000	0.549	0.941	1.000	0.432	0.662	0.000	0.925	0.192	0.771	0.651	0.828	0.000	1.000	0.250	0.694	0.846
2043	0.905	0.602	0.737	0.697	0.543	0.654	0.507	1.000	0.504	0.900	1.000	0.406	0.750	0.000	1.000	0.388	0.851	0.659	0.826	0.154	1.000	0.301	0.951	0.867
2044	0.849	0.367	0.519	0.851	0.532	0.646	0.373	0.874	0.541	0.546	1.000	0.774	0.680	0.000	0.934	0.000	0.539	0.525	0.668	0.191	1.000	0.471	0.559	0.823
2045	0.721	0.436	0.572	0.539	0.766	0.551	0.000	0.815	0.409	0.719	0.941	0.271	0.566	0.000	0.881	0.000	0.818	0.769	0.712	0.000	1.000	0.021	0.774	0.898
2046	0.696	0.463	0.526	0.595	0.604	0.451	0.375	0.764	0.430	0.503	1.000	0.325	0.753	0.000	0.784	0.000	0.562	0.693	0.648	0.000	1.000	0.343	0.332	0.815
2047	0.716	0.712	0.851	0.502	0.737	0.550	0.349	0.871	0.270	0.428	1.000	0.166	0.699	0.000	0.897	0.000	0.552	0.756	0.751	0.000	1.000	0.000	0.362	0.970
2048	0.825	0.988	0.604	0.591	0.635	0.588	0.222	1.000	0.316	0.565	1.000	0.209	0.731	0.000	1.000	0.000	0.765	0.877	0.744	0.000	1.000	0.047	0.482	0.994
2049	1.000	0.815	0.480	0.643	0.662	0.367	0.522	1.000	0.456	0.690	1.000	0.257	0.622	0.000	1.000	0.000	0.660	0.860	0.609	0.064	1.000	0.252	0.631	1.000
2050	0.797	0.682	0.373	0.586	0.481	0.484	0.200	0.998	0.383	0.427	1.000	0.323	0.588	0.000	1.000	0.000	0.521	0.751	0.587	0.000	1.000	0.172	0.623	0.856

Figure 3-20. Water availability (mining – 1% exceedance probability).

3.2.2 Agricultural Impacts

The Sandia hydrological model contains an agriculture-productivity component that estimates the impacts on agriculture from climate change. The algorithms in the hydrological model are based on the work of McCarl et al. (2008) and consider temperature and its standard deviation, precipitation and its standard deviation, and precipitation intensity. The algorithms also recognize soil types for six geographical regions covering CONUS. Implicitly, the model captures minor changes in farming practices (such as fertilizer use or crop rotation) that have been used in response to varying weather/climatic conditions as embodied in the historical data. Because the McCarl work includes time-series analyses as well as panel analyses of crop production within states, it implicitly captures technological and resource usage (such as the use of more or less fertilizer or modified planting regime) associated with variations in climatically induced weather conditions. The model does not include the impacts from increased CO_2 concentrations; only a single CO_2 concentration is used. Because our analysis is solely based on the single A1B IPCC scenario, we do not address changes in CO_2. Therefore, even if we included CO_2 concentration impacts on agriculture, the CO_2 impact would be the same across all the simulations. It would have no effect on the differential impacts of concern to us. Other studies primarily consider one or only a couple of the terms included here (Schlenker et al. 2005; Schlenker and Roberts 2006; Parry et al. 1999; Iglesias et al. 2000). More-detailed dynamic simulations of agricultural impacts also exist (Williams et al. 1984).

The statistical regression underlying McCarl's algorithms uses annual values to optimize predictive capability. This feature of using annual data ensures that the McCarl work embodied in the hydrological model is compatible with our study. The McCarl work is designed to estimate the impact of climate change on agriculture. In our study, we focus on comparing climatic conditions that could realistically occur with historical climate values, which are represented by the climate referent that assumes no climate change. We use the agricultural algorithms to compare crop output across exceedance-probability simulations with changing precipitation conditions from 2010 to 2050. We additionally include agricultural production impacts due to the reallocation (or rights-purchase) of irrigation water away from agricultural activities toward higher-value economic activities such as power generation, industrial needs, and municipal use. Because of their economic dominance, we use corn and soy as the representative crops upon which all agriculture is proportionally reduced in the macroeconomic portion of our analysis. The impact by state is based on its agricultural crop mix and the local impacts of climate.

Reduced agricultural activity results in lost employment as well as lost demand for the intermediate products and goods used by agriculture. These impacts across sectors are readily simulated within the REMI PI+ model, as discussed in Section 3.3. Any reduction in agricultural production is assumed to be made up with imports. The hydrological assessment of agriculture includes improvements in agricultural technology but does not assume that additional agricultural acreage will be available to augment the reduced productivity resulting from climate change. Conversely, we assume historical urban growth trends will cease and reduce the historical rate of farmland conversion in the future. That is, we are assuming there is no significant increase or decrease in farmland acreage in the future.

Figure 3-21 shows an example of the impacts of climate change from 2010 to 2050 on corn production at the 1% exceedance probability. The change in colors helps visualize the variation in impacts of climate change across the years on a state-by-state basis. In this worst-case simulation, the impact on Missouri becomes noticeable in the 2030 time frame (yellow) and continues to become more stressed (orange) through 2050 as typically less and less water is available for growing crops. The 50% exceedance-probability impacts, which are not shown, are not significantly different from the 1% exceedance-probability impacts because the fixed volatility of precipitation and temperature contained in the motif dominates the crop response. States with no significant agriculture show no change in Figure 3-21 (maintain an index of 1.0) despite reduced water availability. The direct economic value of the crop impacts is small compared with the direct economic value of industry impacts from reduced precipitation.

Year	AL	AZ	AR	CA	CO	CT	DE	DC	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
2010	0.968	0.959	0.988	0.997	1.013	0.950	0.970	1.000	0.935	0.945	0.996	1.004	1.002	1.000	1.000	0.971	0.991	0.957	0.969	0.963	0.996	0.990	0.997	1.003	1.011
2011	0.884	0.959	0.940	0.990	1.019	0.891	0.935	1.000	0.843	0.859	1.002	0.987	0.982	0.981	0.976	0.916	0.938	0.904	0.931	0.914	0.963	0.964	0.949	0.988	1.039
2012	0.887	0.906	0.941	0.946	1.012	0.836	0.892	1.000	0.750	0.830	0.984	0.974	0.964	0.967	0.962	0.870	0.930	0.856	0.886	0.872	0.946	0.965	0.963	0.967	1.048
2013	0.838	0.974	0.896	0.895	1.050	0.806	0.875	1.000	0.756	0.806	1.041	0.972	0.976	0.962	0.987	0.863	0.915	0.860	0.869	0.865	0.957	0.945	0.941	0.962	1.093
2014	0.847	1.025	0.869	0.943	1.025	0.737	0.834	1.000	0.642	0.753	0.967	0.969	0.967	0.895	0.848	0.823	0.851	0.795	0.823	0.809	0.906	0.861	0.933	0.938	1.043
2015	0.752	0.747	0.754	0.778	0.947	0.754	0.844	1.000	0.574	0.687	0.954	0.944	0.940	0.918	0.888	0.775	0.862	0.767	0.838	0.815	0.917	0.899	0.876	0.915	1.047
2016	0.744	0.704	0.800	0.758	1.070	0.775	0.851	1.000	0.522	0.647	0.997	0.971	0.965	0.948	0.935	0.824	0.871	0.832	0.847	0.852	0.940	0.926	0.886	0.936	1.090
2017	0.763	0.903	0.874	1.108	1.102	0.775	0.851	1.000	0.611	0.650	1.110	0.990	0.986	0.964	0.973	0.826	0.881	0.811	0.843	0.843	0.959	0.958	0.914	0.976	1.159
2018	0.760	0.790	0.835	0.907	1.045	0.720	0.813	1.000	0.494	0.664	1.014	0.944	0.936	0.919	0.898	0.785	0.887	0.756	0.805	0.790	0.908	0.888	0.907	0.922	1.083
2019	0.809	1.006	0.880	0.922	1.066	0.726	0.839	1.000	0.672	0.716	0.960	0.977	0.979	0.954	0.984	0.827	0.896	0.752	0.831	0.792	0.923	0.921	0.952	0.976	1.071
2020	0.805	1.011	0.899	0.945	1.048	0.735	0.821	1.000	0.604	0.690	0.990	0.968	0.961	0.926	0.919	0.820	0.886	0.827	0.816	0.833	0.935	0.898	0.940	0.948	1.048
2021	0.819	0.699	0.931	0.743	1.028	0.780	0.858	1.000	0.598	0.741	1.002	0.976	0.962	0.959	0.996	0.851	0.884	0.818	0.850	0.859	0.941	0.951	0.933	0.988	1.068
2022	0.735	0.873	0.881	1.004	1.030	0.755	0.841	1.000	0.586	0.652	0.990	0.988	0.976	0.953	0.957	0.793	0.869	0.794	0.836	0.825	0.940	0.912	0.895	0.987	1.045
2023	0.828	0.694	0.915	0.976	1.055	0.655	0.787	1.000	0.675	0.748	1.001	0.965	0.950	0.935	0.946	0.786	0.916	0.683	0.770	0.694	0.918	0.932	0.950	0.967	1.111
2024	0.836	0.885	0.906	0.844	1.066	0.745	0.852	1.000	0.609	0.737	0.941	1.005	1.000	0.981	0.973	0.886	0.910	0.771	0.845	0.795	0.925	0.931	0.964	1.001	1.027
2025	0.827	0.808	0.962	0.826	1.075	0.687	0.795	1.000	0.624	0.744	0.958	0.997	0.992	0.975	0.987	0.826	0.950	0.727	0.787	0.752	0.960	0.950	0.963	1.001	1.046
2026	0.800	0.757	0.935	0.775	1.082	0.710	0.831	1.000	0.615	0.703	1.022	0.995	0.989	0.958	0.966	0.856	0.912	0.745	0.825	0.774	0.948	0.912	0.944	0.989	1.085
2027	0.756	0.829	0.895	0.651	1.071	0.726	0.820	1.000	0.595	0.667	0.926	0.949	0.947	0.916	0.951	0.805	0.864	0.761	0.811	0.793	0.897	0.912	0.905	0.932	1.076
2028	0.731	0.869	0.831	0.914	1.087	0.717	0.801	1.000	0.534	0.642	1.112	0.930	0.927	0.911	0.927	0.756	0.839	0.746	0.793	0.776	0.878	0.866	0.862	0.917	1.095
2029	0.681	0.746	0.718	0.739	0.955	0.647	0.772	1.000	0.488	0.616	0.956	0.960	0.951	0.932	0.863	0.762	0.785	0.726	0.761	0.725	0.939	0.937	0.802	0.918	1.071
2030	0.753	0.821	0.839	0.959	1.006	0.701	0.789	1.000	0.558	0.669	0.986	0.960	0.968	0.940	0.935	0.754	0.889	0.782	0.782	0.783	0.955	0.931	0.916	0.935	1.068
2031	0.703	0.856	0.826	0.875	1.035	0.713	0.810	1.000	0.522	0.646	1.044	0.958	0.968	0.917	0.893	0.793	0.870	0.740	0.804	0.769	0.914	0.894	0.885	0.916	1.113
2032	0.676	0.904	0.782	0.975	1.079	0.691	0.794	1.000	0.632	0.655	0.982	0.951	0.949	0.918	0.937	0.760	0.828	0.738	0.782	0.748	0.920	0.912	0.838	0.930	1.090
2033	0.648	0.865	0.700	0.999	1.017	0.710	0.791	1.000	0.501	0.597	1.008	0.947	0.954	0.912	0.878	0.711	0.818	0.767	0.784	0.785	0.919	0.910	0.820	0.881	1.084
2034	0.711	0.862	0.816	0.869	1.029	0.733	0.814	1.000	0.508	0.630	0.981	0.882	0.880	0.859	0.917	0.760	0.876	0.760	0.803	0.788	0.840	0.848	0.857	0.884	1.010
2035	0.621	0.809	0.692	0.795	1.049	0.650	0.795	1.000	0.474	0.552	1.006	0.965	0.971	0.942	0.888	0.732	0.802	0.708	0.790	0.712	0.926	0.904	0.811	0.929	1.116
2036	0.664	0.727	0.739	0.745	0.933	0.709	0.784	1.000	0.515	0.600	0.940	0.940	0.957	0.895	0.830	0.758	0.814	0.761	0.783	0.782	0.947	0.888	0.835	0.898	1.045
2037	0.749	0.682	0.738	0.731	1.042	0.718	0.830	1.000	0.571	0.694	1.006	0.959	0.979	0.906	0.900	0.757	0.835	0.761	0.820	0.773	0.902	0.877	0.874	0.935	1.114
2038	0.792	0.804	0.910	0.856	1.113	0.700	0.803	1.000	0.543	0.691	1.074	0.980	0.987	0.935	0.951	0.796	0.908	0.741	0.796	0.763	0.939	0.904	0.941	0.967	1.146
2039	0.743	0.953	0.836	0.850	1.113	0.615	0.756	1.000	0.610	0.673	1.087	0.990	0.982	0.948	0.913	0.757	0.894	0.655	0.746	0.675	0.946	0.912	0.891	0.963	1.185
2040	0.680	0.697	0.784	0.738	1.043	0.693	0.785	1.000	0.470	0.607	1.095	0.977	0.966	0.955	0.921	0.727	0.864	0.758	0.777	0.767	0.935	0.932	0.857	0.958	1.152
2041	0.649	0.823	0.733	0.763	1.018	0.629	0.743	1.000	0.436	0.633	0.997	0.942	0.955	0.881	0.870	0.675	0.821	0.701	0.733	0.697	0.903	0.838	0.816	0.886	1.080
2042	0.584	0.726	0.799	1.040	1.036	0.651	0.758	1.000	0.512	0.554	0.995	0.965	0.967	0.921	0.950	0.714	0.830	0.713	0.750	0.718	0.920	0.897	0.844	0.952	1.082
2043	0.555	0.755	0.719	0.837	0.983	0.585	0.704	1.000	0.464	0.518	1.006	0.953	0.951	0.927	0.924	0.665	0.798	0.630	0.691	0.646	0.907	0.891	0.804	0.936	1.105
2044	0.657	0.661	0.707	0.752	1.017	0.619	0.746	1.000	0.533	0.597	1.026	0.907	0.913	0.894	0.860	0.687	0.787	0.649	0.736	0.691	0.887	0.881	0.807	0.862	1.102
2045	0.591	0.922	0.773	0.763	1.096	0.692	0.779	1.000	0.466	0.565	1.092	0.973	0.976	0.949	0.876	0.704	0.820	0.747	0.768	0.754	0.972	0.937	0.828	0.940	1.137
2046	0.662	0.889	0.764	0.845	1.041	0.634	0.760	1.000	0.429	0.595	1.114	0.931	0.937	0.891	0.860	0.694	0.825	0.694	0.755	0.703	0.904	0.872	0.831	0.901	1.161
2047	0.557	0.908	0.627	0.994	1.053	0.602	0.707	1.000	0.443	0.483	1.112	0.865	0.900	0.825	0.809	0.600	0.767	0.702	0.697	0.700	0.859	0.819	0.739	0.822	1.168
2048	0.512	0.973	0.666	1.150	1.118	0.594	0.691	1.000	0.403	0.446	1.105	0.923	0.934	0.898	0.903	0.594	0.780	0.677	0.680	0.682	0.893	0.879	0.748	0.900	1.170
2049	0.545	0.849	0.703	0.995	1.114	0.677	0.773	1.000	0.479	0.522	0.996	0.976	0.980	0.936	0.943	0.721	0.748	0.732	0.764	0.751	0.928	0.912	0.748	0.936	1.078
2050	0.588	0.829	0.625	0.956	0.993	0.618	0.729	1.000	0.403	0.545	0.990	0.940	0.954	0.928	0.860	0.654	0.802	0.702	0.723	0.701	0.940	0.904	0.773	0.889	1.113

Year	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
2010	0.999	1.008	0.959	0.970	0.973	0.964	0.953	0.986	0.999	0.974	1.010	0.961	0.950	0.946	0.992	0.964	0.965	0.989	0.961	0.961	1.005	0.958	0.996	1.014
2011	0.977	1.029	0.907	0.933	0.969	0.897	0.899	0.956	0.976	0.907	1.047	0.907	0.900	0.881	0.957	0.898	0.912	1.001	0.901	0.914	1.024	0.901	0.970	1.018
2012	0.968	1.002	0.858	0.895	0.931	0.852	0.853	0.977	0.944	0.847	1.029	0.849	0.848	0.833	0.961	0.876	0.862	0.966	0.854	0.858	1.024	0.838	0.961	1.011
2013	0.965	1.049	0.851	0.876	0.961	0.848	0.843	0.932	0.978	0.882	1.122	0.834	0.819	0.837	0.939	0.849	0.905	1.004	0.847	0.835	1.121	0.819	0.954	1.075
2014	0.832	1.044	0.789	0.829	0.951	0.782	0.775	0.807	0.956	0.751	1.065	0.759	0.744	0.749	0.827	0.799	0.797	0.972	0.802	0.799	1.064	0.767	0.900	1.019
2015	0.882	1.018	0.790	0.846	0.759	0.795	0.755	0.907	0.936	0.702	1.006	0.781	0.761	0.710	0.890	0.710	0.737	0.802	0.789	0.798	0.948	0.767	0.913	0.992
2016	0.959	1.057	0.832	0.867	0.828	0.839	0.740	0.927	0.955	0.777	1.103	0.823	0.779	0.685	0.927	0.744	0.814	0.793	0.835	0.809	1.090	0.798	0.943	1.072
2017	0.978	1.135	0.819	0.860	1.044	0.816	0.731	0.951	0.971	0.798	1.182	0.804	0.790	0.676	0.965	0.787	0.816	1.018	0.818	0.796	1.153	0.772	0.964	1.134
2018	0.906	1.135	0.765	0.816	0.821	0.770	0.745	0.861	0.931	0.687	1.122	0.756	0.745	0.697	0.872	0.749	0.750	0.981	0.764	0.773	1.056	0.747	0.915	1.052
2019	0.976	0.997	0.768	0.828	1.017	0.765	0.787	0.919	0.964	0.776	1.040	0.777	0.735	0.750	0.942	0.804	0.795	0.979	0.753	0.811	1.047	0.778	0.921	1.060
2020	0.910	1.010	0.816	0.837	0.967	0.810	0.756	0.881	0.947	0.838	1.092	0.786	0.744	0.722	0.891	0.815	0.887	0.990	0.814	0.778	1.057	0.755	0.926	1.063
2021	0.992	1.071	0.833	0.865	0.807	0.820	0.800	0.964	0.937	0.860	1.040	0.802	0.802	0.767	0.953	0.835	0.791	0.783	0.825	0.835	1.040	0.801	0.954	1.043
2022	0.957	1.092	0.800	0.845	0.810	0.797	0.723	0.863	0.970	0.767	1.108	0.783	0.770	0.679	0.911	0.765	0.765	1.018	0.797	0.775	1.059	0.750	0.937	1.090
2023	0.952	1.003	0.675	0.757	0.762	0.652	0.787	0.926	0.922	0.836	1.039	0.657	0.685	0.768	0.911	0.813	0.767	1.002	0.654	0.755	1.026	0.703	0.936	1.076
2024	0.975	0.981	0.773	0.842	0.913	0.777	0.809	0.897	0.978	0.843	1.030	0.790	0.756	0.770	0.929	0.860	0.822	0.957	0.777	0.828	1.022	0.817	0.945	1.040
2025	0.981	1.032	0.732	0.783	0.908	0.732	0.763	0.938	0.984	0.928	1.041	0.727	0.703	0.749	0.948	0.831	0.893	0.911	0.722	0.763	0.986	0.741	0.967	1.028
2026	0.940	1.136	0.754	0.817	0.847	0.774	0.788	0.905	0.970	0.849	1.153	0.774	0.714	0.751	0.904	0.816	0.788	0.871	0.768	0.814	1.108	0.790	0.943	1.089
2027	0.923	1.118	0.771	0.813	0.871	0.775	0.761	0.913	0.932	0.796	0.943	0.751	0.751	0.717	0.904	0.782	0.731	0.879	0.774	0.784	1.010	0.745	0.905	1.082
2028	0.912	1.114	0.754	0.814	0.792	0.763	0.721	0.856	0.916	0.692	1.136	0.746	0.723	0.680	0.865	0.745	0.648	1.042	0.756	0.740	1.104	0.708	0.889	1.117
2029	0.903	1.054	0.715	0.750	0.720	0.731	0.729	0.921	0.921	0.620	1.041	0.686	0.657	0.681	0.909	0.700	0.668	0.699	0.733	0.726	1.012	0.687	0.942	0.997
2030	0.944	1.070	0.768	0.786	0.754	0.782	0.712	0.908	0.961	0.677	1.078	0.726	0.721	0.688	0.909	0.735	0.707	0.952	0.783	0.730	1.059	0.695	0.942	1.072
2031	0.942	1.092	0.746	0.810	0.823	0.770	0.729	0.872	0.969	0.671	1.116	0.758	0.730	0.689	0.899	0.748	0.694	0.960	0.757	0.769	1.110	0.751	0.904	1.097
2032	0.903	1.084	0.729	0.782	0.878	0.746	0.727	0.885	0.934	0.783	1.104	0.708	0.700	0.692	0.891	0.715	0.789	0.962	0.745	0.735	1.082	0.699	0.921	1.067
2033	0.892	1.035	0.767	0.801	0.829	0.751	0.697	0.890	0.942	0.627	1.053	0.727	0.727	0.642	0.883	0.620	0.709	0.974	0.760	0.730	1.056	0.701	0.918	1.079
2034	0.886	1.075	0.765	0.812	0.911	0.752	0.709	0.823	0.867	0.784	1.116	0.725	0.763	0.660	0.828	0.710	0.805	0.833	0.755	0.755	1.049	0.714	0.836	0.979
2035	0.928	1.088	0.698	0.781	0.808	0.713	0.699	0.889	0.960	0.584	1.093	0.734	0.656	0.630	0.908	0.657	0.606	0.888	0.705	0.761	1.064	0.717	0.922	1.093
2036	0.831	1.019	0.763	0.799	0.777	0.789	0.712	0.833	0.961	0.630	1.057	0.759	0.708	0.664	0.839	0.691	0.675	0.779	0.781	0.758	1.066	0.747	0.926	1.004
2037	0.913	1.080	0.753	0.829	0.833	0.756	0.755	0.888	0.969	0.686	1.075	0.764	0.719	0.719	0.867	0.712	0.702	0.815	0.757	0.784	1.066	0.737	0.885	1.054
2038	0.947	1.144	0.745	0.793	0.904	0.747	0.739	0.897	0.956	0.788	1.182	0.729	0.714	0.713	0.894	0.799	0.831	0.945	0.746	0.754	1.192	0.731	0.924	1.134
2039	0.903	1.100	0.655	0.730	0.890	0.670	0.709	0.891	0.967	0.696	1.190	0.661	0.622	0.690	0.891	0.732	0.754	1.062	0.659	0.715	1.202	0.684	0.944	1.144
2040	0.910	1.182	0.752	0.794	0.778	0.762	0.677	0.931	0.957	0.697	1.193	0.734	0.691	0.629	0.930	0.673	0.752	0.808	0.771	0.736	1.172	0.703	0.944	1.168
2041	0.822	1.121	0.682	0.732	0.885	0.670	0.699	0.815	0.941	0.679	1.139	0.659	0.655	0.665	0.786	0.633	0.711	0.851	0.675	0.694	1.095	0.647	0.877	1.039
2042	0.895	1.092	0.703	0.755	0.863	0.686	0.662	0.883	0.958	0.738	1.129	0.688	0.666	0.606	0.873	0.638	0.711	0.745	0.707	0.696	1.099	0.651	0.913	1.033
2043	0.908	1.068	0.628	0.680	0.795	0.624	0.620	0.888	0.918	0.704	1.125	0.592	0.604	0.561	0.890	0.562	0.687	0.775	0.630	0.645	1.089	0.582	0.913	1.072
2044	0.870	1.111	0.669	0.737	0.799	0.666	0.652	0.853	0.912	0.586	1.163	0.664	0.647	0.612	0.839	0.643	0.617	0.697	0.667	0.677	1.133	0.637	0.886	1.033
2045	0.878	1.106	0.739	0.784	0.949	0.737	0.666	0.914	0.970	0.700	1.159	0.706	0.694	0.608	0.885	0.598	0.758	0.920	0.743	0.713	1.164	0.674	0.972	1.109
2046	0.843	1.120	0.687	0.754	0.860	0.701	0.687	0.870	0.938	0.601	1.197	0.705	0.661	0.628	0.833	0.637	0.664	0.858	0.696	0.712	1.181	0.680	0.894	1.068
2047	0.821	1.163	0.688	0.704	0.936	0.673	0.600	0.822	0.910	0.531	1.237	0.624	0.637	0.522	0.832	0.540	0.639	0.911	0.689	0.636	1.225	0.592	0.820	1.144
2048	0.864	1.089	0.666	0.686	0.885	0.639	0.577	0.840	0.935	0.612	1.156	0.599	0.636	0.500	0.810	0.525	0.707	1.008	0.661	0.618	1.158	0.570	0.890	1.158
2049	0.936	1.040	0.731	0.781	0.896	0.735	0.664	0.869	0.970	0.670	1.123	0.716	0.684	0.600	0.889	0.610	0.686	0.916	0.739	0.726	1.132	0.702	0.936	1.096
2050	0.895	1.089	0.688	0.725	0.778	0.687	0.642	0.898	0.961	0.544	1.109	0.656	0.629	0.591	0.895	0.576	0.638	0.842	0.691	0.682	1.081	0.645	0.933	1.045

Figure 3-21. Water impacts (corn – 1% exceedance probability).

3.2.3 Costs of Water Transfer

Our analysis recognizes the practice of transferring water rights through contractual or policy means, typically from agricultural entities. While we do estimate these costs, they are not explicitly added to the macroeconomic analysis for three reasons. One reason is that the actual costs may not be less substantial than those costs estimated here, especially if policy interventions limit the prices of water transfer. A second reason is that climate change may reduce the economic viability of agricultural activities and result in water normally used for farming being available for other uses. Such conditions are apparent today when upstream or urban water usage exceeds the amount that would be formally associated with existing rights held by the urban areas. In effect, cities are often using more water than they have the right to use, while farmers are often using less water than they have the right to use. A third and very important reason for not explicitly adding the costs of water transfer to the macroeconomic analysis is that a macroeconomic model categorizes economic activity by economic sectors.

The selling of water rights by the agricultural or mining sector is not related to added agricultural or mining activity. We consider such sales as an added "water-utility" activity that is already accounted for in our analysis. Thus, in an economic sense, the "water sector" is merely buying and selling from itself. The cost of increased water delivery is accounted for in the macroeconomic simulation (albeit, in the version of the REMI model we use, all distribution utilities are lumped together as a single economic entity for each state). The cost of procuring water, whether by new wells or new water rights, is implicitly contained in the model's logic. Therefore we have not attempted to explicitly make any exogenous (external), and potentially redundant, correction to the macroeconomic model simulation.

To verify the adequacy of these assumptions, we estimate the cost of water transfer based on a cost of $1,000 per acre-foot of deliverable water (as opposed to just water rights). This cost is consistent with existing transactions and with expectations over this time frame (SeekingAlpha 2007; Frederick and Schwarz 2000). The aggregated national-level water transfer costs over the 2010 to 2050 period for varying exceedance probabilities are shown in Figure 3-22.

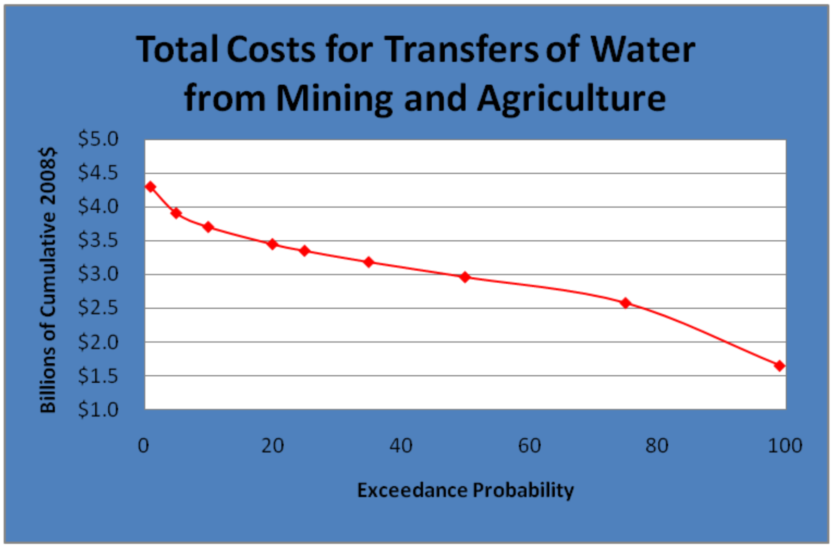

Figure 3-22. Water transfer costs.

Thus, at a 50% exceedance probability, the cost to purchase water from the mining and agriculture sectors over the 40-year period would be approximately $3 billion. The highest cost, at the 1% exceedance probability, would be approximately $4.3 billion. These costs are negligible compared with the primary economic impacts across the simulations.

3.2.4 Water Availability in the Hydrological Referent

When we apply the macroeconomic referent to the hydrological model in the absence of additional climate change, simulation results show that the "normal" water supply will be inadequate to meet projected demand for water in several regions of the United States. Other researchers also realize the potential for shortages even in an assumed business-as-usual environment (Frederick and Schwarz 2000; EPA 2002; GAO 2003; Karl et al. 2009; NRC 2004; USBR 2005). This concern is widely appreciated (USBR 2005) but is not included in macroeconomic models because such models are necessarily parameterized to assume that physical conditions remain unchanged from historical values. As such, the analysis presented here only considers water availability conditions in excess of those beyond what would occur under the hydrological referent. For reference, in Appendix C, we present and summarize the implied impacts of water scarcity even in the absence of climate change.

3.3 Macroeconomic Simulation

For the economic component of our risk assessment, we use the Regional Economic Models Incorporated (REMI 2009) PI+ model, usually simply noted as the REMI model. The pragmatic state-focused perspective of our work limits the study to the risk assessment between the years 2010 and 2050. The macroeconomic forecast contained in the REMI model is the U.S. Department of Commerce's Bureau of Economic Analysis (BEA) forecast extended to 2050. This forecast and the REMI model are used within many states for policy and impact analysis (REMI 2007; Treyz and Treyz 2004). Although the REMI model has an admirable track record for predictive accuracy, our use of the forecast is not based on its potential accuracy. Instead, we use this macroeconomic referent as a common basis for policy discussions, simply as a point of comparison with the results simulated in our analysis. The REMI model is robust from a policy-outcome perspective in that the differences it produces between a base case and simulations that assume alternative values of input parameters maintain a coherent relationship among parameters and their impact on results. In other words, the REMI model effectively characterizes how one set of inputs is preferable to another set of inputs. Additionally, in a historical sense, simulated results from the REMI model have been consistent with impacts observed from actual policy initiatives or historical economic shocks.

3.3.1 Economic Impact Analysis in Context

The economic impact analysis is the last step in the three-step overall analysis process presented previously in Figure 1-2. To recap, the first step in the overall analysis process involves a climatic analysis where we determine a set of hydrological and macroeconomic simulations of potential climatic futures for precipitation and temperature conditions to execute based on the uncertainty indicated in the PCMDI data. Each of these simulations represents a different exceedance probability taken from the national precipitation distribution (Figure 3-7). We then adjust the MIROC3.2 model precipitation forecast for each state from 2010 to 2050, inclusively, by the ratio of (the PCMDI ensemble's) median historical precipitation to the precipitation value indicated in Table 3-1. These precipitation levels are the output of the climatic analysis and the input to the hydrological model.

In the second step of our overall analysis process, we conduct a hydrological analysis, where we employ the hydrological model to produce the availability of water for industrial, mining, power generation, and municipal uses. The hydrological analysis further determines the change in agricultural output due to the changing climatic conditions. The water availability and agricultural production are the output of the hydrological analysis and the input to the economic impact analysis.

The third step in our overall analysis process is the economic impact analysis. This step consists of two parts. The first part involves premodeling activities to transform the estimated hydrological impacts from the hydrological model into the relevant economic description that the REMI model can use to determine the implications across the entire U.S. economy. Specifically, we convert the physical water availability and change in agricultural production to dollar-based quantity changes in the agricultural demand for goods and services, as well as the increased costs of importing agricultural products to serve the demand not satisfied by domestic production. We convert the water availability to the investments needed to allow continued operation under reduced water-supply conditions. These costs become the actual input values to the second part of the economic impact analysis, which consists of the actual REMI simulations. The REMI model determines the time-dependent interacting industry and interacting state responses at nine different exceedance probabilities. Figure 3-23 depicts the general data flow between the second and third steps of our overall analysis process.

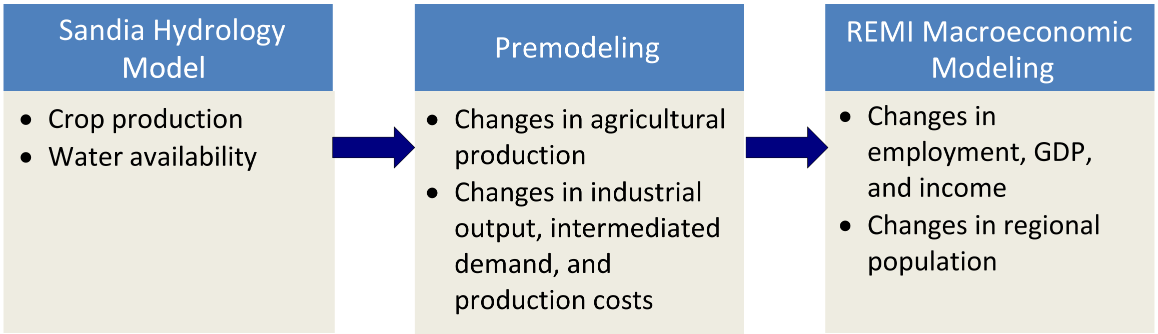

Figure 3-23. Data flow in last two steps of the overall analysis process.

3.3.2 Characteristics and Structure of the REMI Model

The REMI model is a time-dependent macroeconomic forecasting and policy analysis model.[5] It is a mature and well-known model with documentation that includes exhaustive references, especially with regard to model evaluation (REMI 2007).[6] The model is widely used by states and U.S. corporations as noted on its website.[7] The REMI model integrates input-output, computable general equilibrium (CGE), econometric, and economic-geography methodologies. For our study, we use the U.S. version of the REMI model with state-level detail for 70 economic sectors. The input-output aspect of the model captures interindustry changes in demand and production. The CGE aspect of the REMI model instantaneously balances supply and demand through price, but the REMI model also addresses delayed responses due to investments, population/business migration, and wage adjustments that provide a more realistic simulation of the interactions and interdependencies across states and across time than what a strictly optimization-based approach to CGE would indicate. The econometric aspects ensure the model reflects the statistically estimated response characteristics of the individual states.

Figure 3-24 and Figure 3-25 show the overall structure of the PI+ model. The model contains five major blocks: (1) Output; (2) Labor and Capital Demand; (3) Population and Labor Supply; (4) Wages, Prices, and Costs; and (5) Market Shares. The access to factors of production such as labor and specialty commodities can affect how business can respond to local changes in conditions (e.g., due to climate change) by expanding operation in other states. The use of intermediate inputs from other industries ties the national and international economies together with cascading, interacting, multiplicative impacts as individual industries respond to the impacts of climate change.

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[5] The description of the PI+ model in this section is based on material provided by REMI and used with permission.

[6] The evaluations are comparisons to other methods or of prediction versus observations. The reported evaluations do not include the formal verification and validation methods often associated with engineering models attempting to match experimental data.

[7] See http://www.remi.com/index.php?page=by-sector&hl=en_US and www.remi.com.

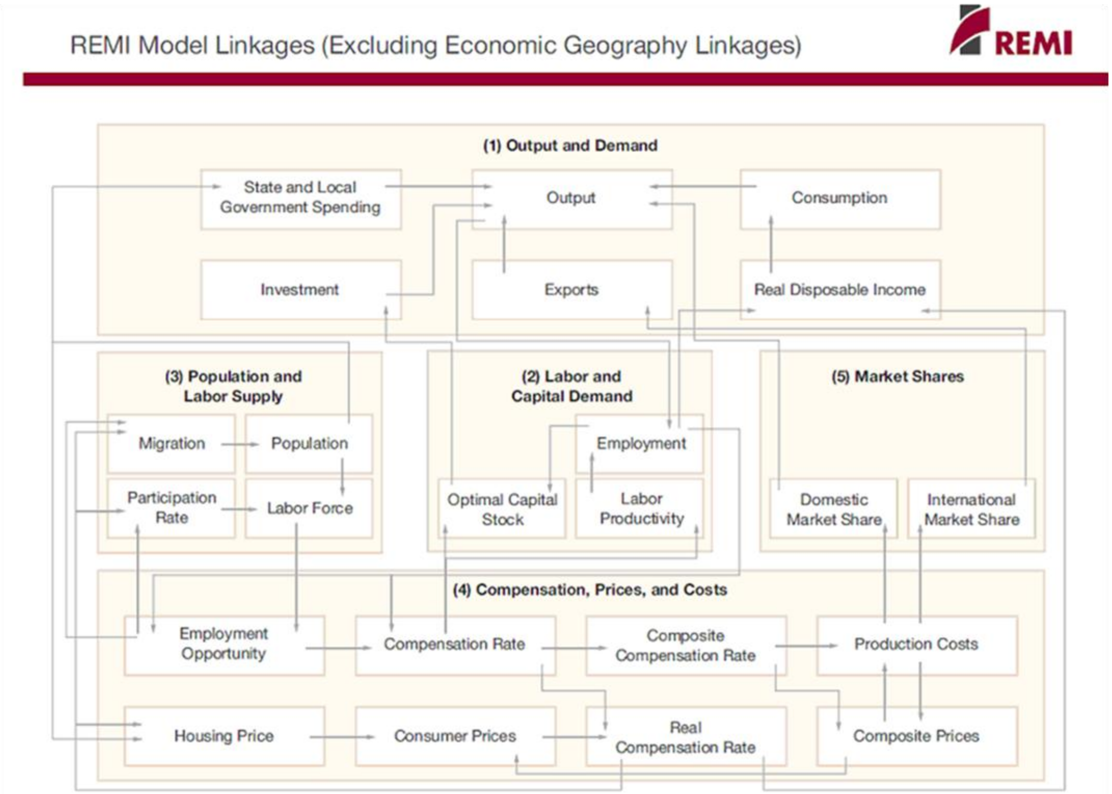

Figure 3-24. REMI PI+ model components and linkages.

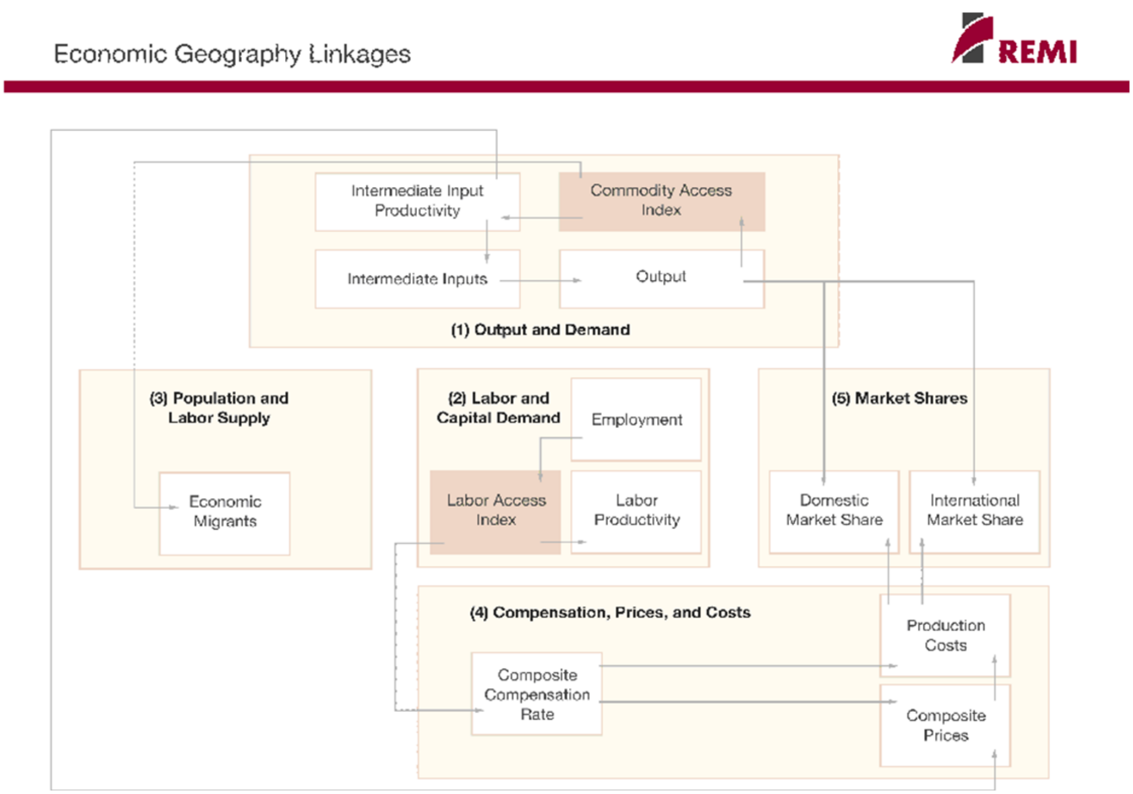

Figure 3-25. REMI PI+ model detail on intermediate demand and factor access.

Several industries are particularly susceptible to changes in water availability, and we explicitly simulate their adjustments to a changing climate and the consequences throughout the economy (Morrison et al. 2009). The industries most directly affected by reduced water availability are as follows:

- Agriculture/farming
- Food
- Beverage
- Paper
- Petroleum and coal
- Chemical
- Primary metal
- Mining
- Thermoelectric power generation
- Hydropower
- Municipal water utilities

See Appendix B for further details about the above industries.

The specific premodeling effort of mapping the hydrological impacts of climate change to the initiating impact on each industry is presented in Appendix B, and a more detailed discussion is presented by Warren et al. (2009). The following bullets briefly summarize how we use the REMI model to calculate impacts:

- The changes in crop productivity from the hydrological model translate to changes in farm demand for secondary products (such as fertilizer) and reduced supply (leading primarily to imports) for sectors that use agricultural products.

- With water shortages, thermoelectric and industrial sectors using cooling-water convert to closed-cycle cooling or even to dry cooling as conditions demand (Kelic et al. 2009; Warren et al. 2009). These changes increase the cost of producing output. Changes in the demand for their products due to increased costs then affect employment and the demand these sectors previously had for products from other industrial sectors, generating a spiral of impacts across industries—a story familiar in the United States during the recent financial crisis.

- For coastal industries, conversion to saline-water use is considered.

- If reduced precipitation affects hydropower production, new generation is built endogenously (i.e., within the REMI model), often in surrounding states to serve the otherwise unsatisfied demand for electricity.

- For industrial consumptive uses of water, if efficiency improvements cannot adequately reduce water needs to match availability, production becomes constrained and declines.

- Given the options for reducing the uses of municipal water (e.g., not watering lawns and adding low-flow appliances) in addition to the general ability of municipal authorities to purchase water rights, the direct economic impact on municipal water consumers is estimated to be minimal.

- If an industry already efficiently uses water, it has less capability to accommodate reduced water availability. The industry has already exercised the majority of options available, and its sensitivity to water shortages is greater than those industries that use water less efficiently. This consideration is particularly apparent in the mining industry.

- Those regions that marginally have adequate water in the present have not yet developed storage and sophisticated water-allocation (water rights) strategies. These areas immediately experience the impact of reduced water availability, even more than those regions that currently deal with (accommodate) water limitations on a routine basis.

4 Analysis Results

The estimated cost of climate change comes ultimately from the macroeconomic analysis. Figure 4-1 presents a conceptual illustration of how the Sandia hydrological model associates levels of precipitation (rainfall) with probabilities. The probabilities are ultimately associated with the water availability that affects the economy. The economic effects are the impacts that the macroeconomic model generates through its simulation of the interacting state-level economies. The probabilities, as illustrated below, and impacts (consequences) are combined to determine the total risk to the economy.

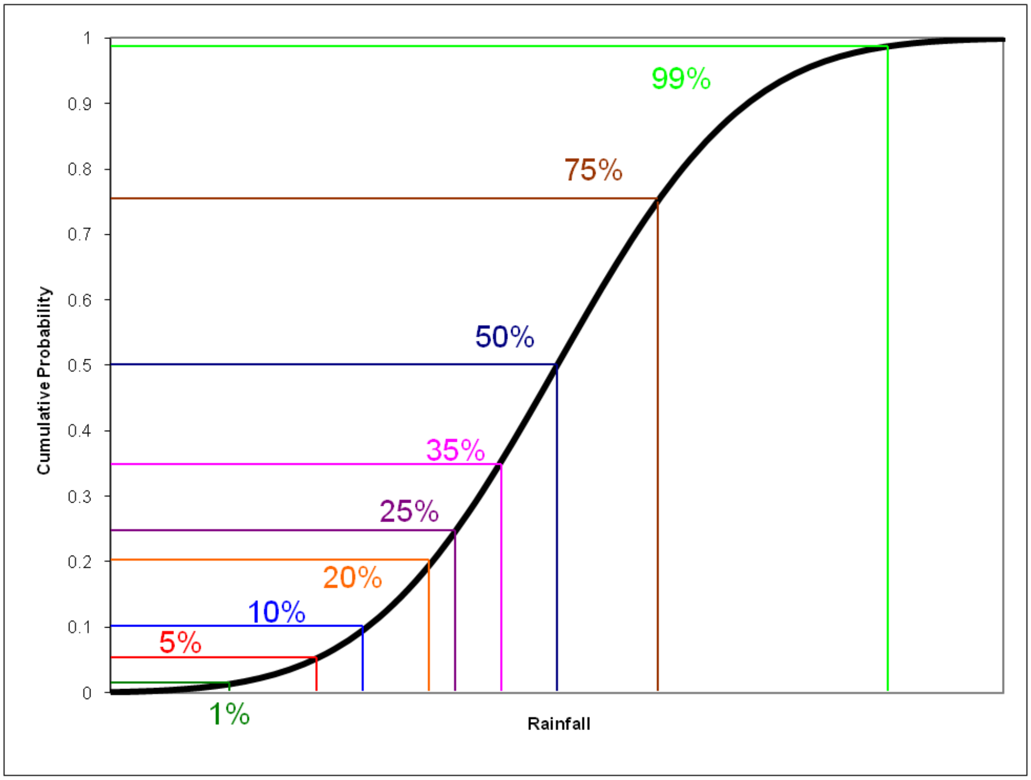

Figure 4-1. An illustration of precipitation conditions sampled from the climate-model ensemble distribution and analyzed in this study.

The dark black line in Figure 4-1 is a stylized representation of the cumulative probability distribution estimated from the climate-change ensemble shown in Figure 3-7. The vertical axis represents the cumulative probability, which can be interpreted as the probability that the precipitation levels will be less than the corresponding point on the horizontal axis, the amount of rainfall. The colored lines denote the lower (50% or less) exceedance probabilities used in the simulations. The basic information that is being conveyed here is that as the probabilities decrease, for example, from 50% to 35%, so does the amount of rainfall (i.e., the location on the horizontal axis for the corresponding precipitation moves to the left, from dark blue to pinkish purple.). For each exceedance probability, the climate models forecast rainfall, and hydrological modeling translates these rainfalls into changes in agricultural productivity and water availability for the economy. The climate referent, which assumes no global climate change, is not pictured in this figure.

Climate change implies declining precipitation in the future at the national level. The precipitation conditions in our climate referent assume no change in average precipitation in the future. Because Figure 4-1 depicts exceedance probabilities for temporal precipitation patterns only relevant to conditions associated with climate change, the constant precipitation conditions assumed in the climate referent cannot be meaningfully portrayed in Figure 4-1. Even though the 99% exceedance-probability simulation may yield more precipitation in some states than does the climate referent, the simulation shows impacts relative to the economic conditions of precipitation in the climate referent. These impacts occur because climate change dominantly affects how the precipitation in one state compared to that of another state diverges from the historical relationship of differences in precipitation among the individual states. At large exceedance probabilities, some states experience increased precipitation compared to historical amounts, while other states experience reduced precipitation—even if the national average precipitation in a simulation is above the climate referent of national precipitation. The states with inadequate precipitation experience economic impacts. Figure 4-1 conceptually depicts national precipitation levels. Our analysis explicitly estimates impacts at the state level. We only use the national-level precipitation as the metric for differentiating the simulations from one another.

Climate change contains volatility in its projection of future conditions, as evident in the motif, whereas the climate referent has constant conditions. On one hand, the difference between a simulation with variable precipitation and one with constant precipitation could seem to spuriously create impacts. As described in Section 3.1.2, the use of an unchanging climate referent is possibly the only defensible choice given the statistical character of the climate model results. More importantly, as implied in Section 4.3, even if volatility ("normal" climate variations) could be included in the climate referent in a manner statistically compatible with the volatility in the climate-model results, the volatility would have a minimal impact on the conclusions in the analysis.

We use the climatic conditions associated with selected exceedance probabilities to calculate the hydrological impacts at the county and state levels, and we use the results of the hydrological model to calculate the direct physical water-availability impacts at the state and industry levels. The water-availability impacts then feed into the REMI macroeconomic model according to the economic methodology described in Appendix B of this report. The results of the macroeconomic modeling at the aggregate national level as well as at the state- and industry-level are discussed below. Regional distinctions about the climate-change impacts will also be evident.

We run the REMI model on an annual basis for the years 2007 to 2050.[8] As a result of the recent global financial crisis, the revised historical estimates of economic activity

[8] Runs of the REMI model assume that Keynesian closure rules are followed, which "[do] not use an interest rate mechanism to correct changes in U.S. employment that have been caused by an exogenous policy shock" (REMI 2009). The other options, which assume "coordination between fiscal and monetary policy makers resulting in interest rate adjustments that would immediately adapt to new policies, so that

may not exactly correspond to the macroeconomic forecast of the base-case referent from the REMI model presented in Appendix D. Nonetheless, the estimates we apply are a usable referent for comparing macroeconomic impacts across different climate regimes. All costs are presented in constant 2008 U.S. dollars.

Following are the results of using the analysis framework developed in the previous sections of this report. Section 4.1 presents the national economic and labor impacts of climate change through the year 2050 in the absence of policy. Section 4.2 describes the impacts across the different economic sectors of the national economy. Section 4.3 addresses the significance of representing climate change with its actual volatility versus treating it as a smooth, long-term trend. Section 4.4 communicates the state-level impacts. Section 4.5 briefly places the results in context.

4.1 National Impacts

This section summarizes the national-level risk assessment of climate-change impacts through the year 2050. Figure 4-2 shows the value of GDP impacts associated with the "best estimate" (solid) line of the distribution for precipitation uncertainty shown in Figure 3-7.

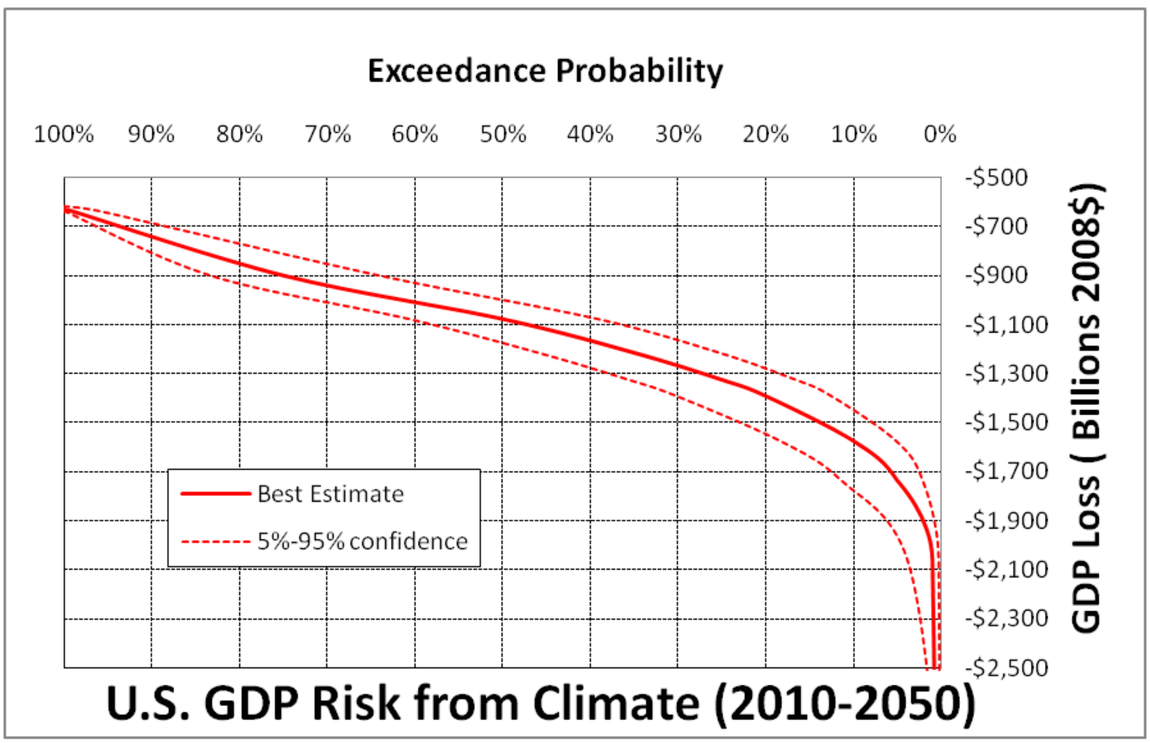

Figure 4-2. U.S. GDP impacts (2010–2050) with confidence intervals for a 0% discount rate.

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employment would be maintained at a constant rate" are deemed inappropriate, especially when the changes to the model will be caused by unpredictable changes in weather and climate.

The dashed lines in Figure 4-2 indicate the second-order uncertainty for macroeconomic impacts associated with the climatic conditions. The dashed lines characterize our knowledge of the uncertainty of the best-estimate values to within 90% confidence, reflecting a lower and an upper limit on the uncertainty, from 5% (lower dashed line) to 95% (upper dashed line). Note that a GDP loss associated with any data point that could be placed outside of the dashed lines (e.g., for a point at 20% probability reflecting a GDP loss in excess of $1.5 trillion) would have a very remote possibility of occurring, given our current understanding.

Table 4-1 presents the value of the GDP loss over different discount rates. The estimated GDP summary risk is $1.2 trillion through 2050 at a 0% discount rate. The summary risk is calculated as the sum of consequence multiplied by the probability over the entire range of exceedance probabilities (100% to 0%). We are discussing these probabilities from highest to lowest because impacts are smallest at a 100% exceedance probability and largest at a 0% exceedance probability. Our text, figures, and tables follow the progression from the largest exceedance probabilities (smallest impacts) to the smallest exceedance probabilities (largest impacts). Though not included in the table, the annual loss to the GDP at the 50% exceedance probability is nearly $60 billion in 2050 and would exceed $130 billion at the 1% exceedance probability. The annual data for the 1% exceedance-probability case is presented in Appendix E.

Table 4-1. GDP Impacts and Summary Risk (2010–2050)

Change in National GDP (Billions of 2008$)										
Discount rate	Exceedance Probability									Summary Risk
	99%	75%	50%	35%	25%	20%	10%	5%	1%	
0.0%	-$638.5	-$899.4	-$1,076.8	-$1,214.5	-$1,324.6	-$1,390.8	-$1,573.9	-$1,735.4	-$2,058.5	-$1,204.8
1.5%	-$432.0	-$595.9	-$707.4	-$795.0	-$865.1	-$907.2	-$1,024.6	-$1,129.3	-$1,340.2	-$790.3
3.0%	-$301.9	-$407.4	-$479.4	-$536.6	-$582.4	-$610.0	-$687.2	-$756.8	-$898.2	-$534.5

The summary risk in Table 4-1 includes both interpolated and extrapolated risks as explained in Section 2.5. The interpolated risk values are based on the simulated values between the 99% and 1% exceedance probabilities in Figure 4-2. The extrapolated risk values, which are outside the range of the 99% and 1% probabilities, are derived estimates of the contribution between the 1% and 0% exceedance probabilities (very severe) and the 100% to 99% exceedance probabilities (the largest amount of precipitation) of Figure 4-2. Given the rapid increase in losses at the lower exceedance probabilities (e.g., 10% to 1%), and the existence of climate-induced loss even at the 100% exceedance probability, the loss at the 50% exceedance probability only modestly underestimates the total risk.

Figure 4-3 shows the impacts on employment measured in lost labor years over the years 2010 to 2050 at various levels of uncertainty. The mean-estimate line is included, bounded by the confidence interval. A labor year is equivalent to having one full-time job for a year.

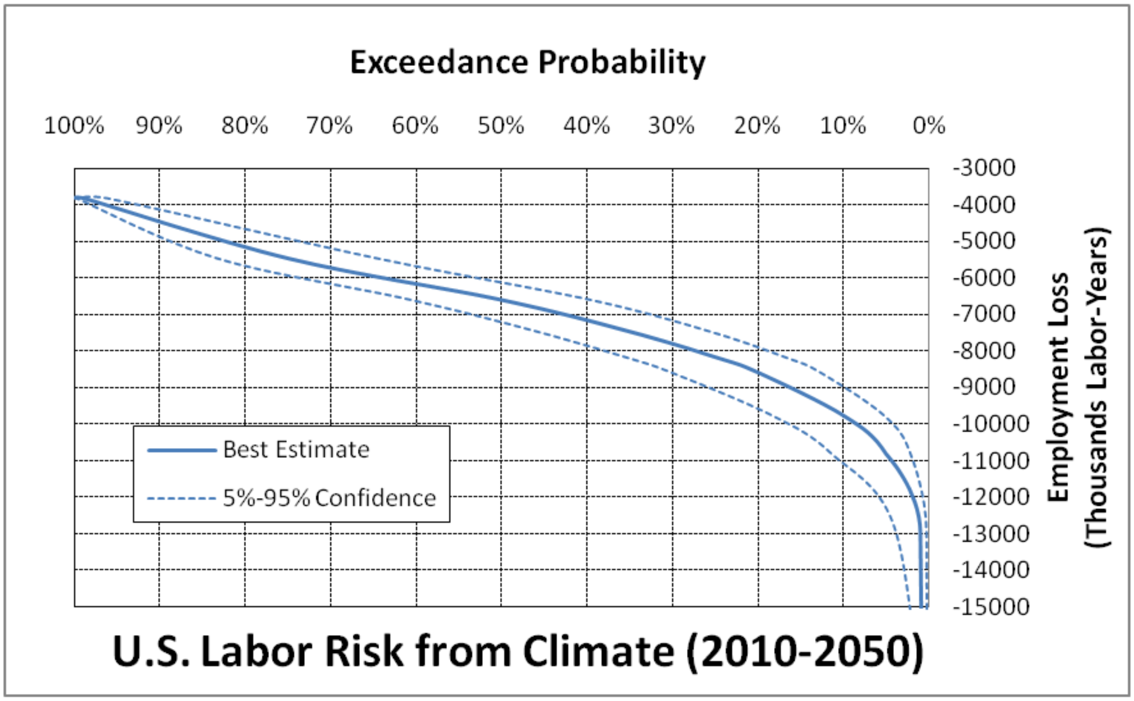

Figure 4-3. U.S. employment impacts (2010–2050).

Table 4-2 shows the employment-loss values associated with the mean-estimate (solid blue) line in Figure 4-3. For the summary risk, the table only includes the interpolated values (99% to 1%). The analysis does not attempt to consider a widespread migration of the unemployed population beyond U.S. borders that is possible at the 1% to 0% extreme. The summary risk is nearly 7 million lost labor years between 2010 and 2050 due to climate change.[9] The annual job loss by 2050 at the 50% exceedance probability is nearly 320,000 full-time jobs. At the 1% exceedance probability for the same year, the annual job loss rises to nearly 700,000 full-time jobs. The uncertainty in the employment impacts due to second-order climatic uncertainty changes the results by no more than approximately 10%.

Table 4-2. Employment Impacts and Summary Risk (2010–2050)

Change in Employment (Thousands)									
Exceedance Probability									Summary Risk
99%	75%	50%	35%	25%	20%	10%	5%	1%	
-3,815	-5,463	-6,601	-7,468	-8,166	-8,587	-9,764	-10,819	-12,961	-6,863

[9] Again, the monetary and labor values noted as risks are the sum (approximate integral) of consequence at different exceedance probabilities over the entire (100% to 0%) range of probabilities.

When water availability limits economic production within the United States, one alternative is to import the lost commodities, especially food. Figure 4-4 shows the impact of climate change on the U.S. trade balance, without the second-order uncertainty region. This study is U.S. centric and assumes that the rest of the world can accommodate added U.S. demands for imports. Our analysis implicitly assumes the ability of the rest of the world to import and export products at the costs assumed in the macroeconomic referent. This assumption is assuredly unrealistic and influences the uncertainty in our forecasted impacts. Because we have not analyzed this uncertainty factor as part of this study, the forecast uncertainty is not presented in Figure 4-4. Nonetheless, the change in net exports (gross exports minus gross imports) is still a useful way to illustrate the potential impacts of reduced U.S. production and competitiveness.

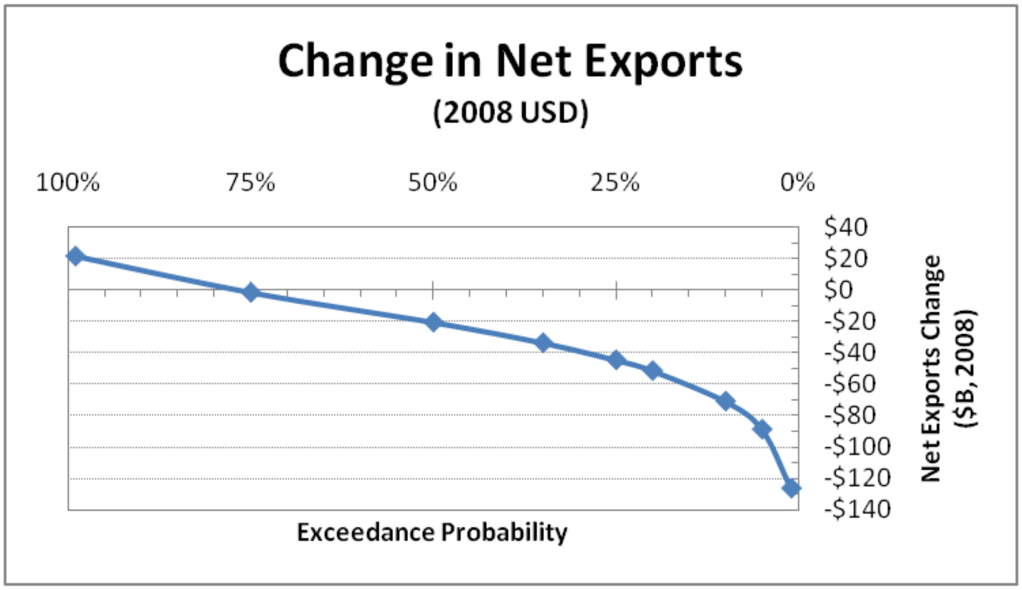

Figure 4-4. Trade balance impacts (2010–2050) (0% discount, interpolated).

Assuming that the financial markets in the rest of the world can accommodate increased U.S. demands, the U.S. trade imbalance only expands (gets worse) by an additional $0.5 billion per year in 2050 at the 50% exceedance probability and by an additional $8 billion per year at the 1% exceedance probability. While it seems likely that this forecast is underestimated, the trade balance risk from 2010 to 2050 is over $25 billion at a 0% discount rate. The trade balance impacts for the three discount rates are presented in Table 4-3.

Table 4-3. Balance of Trade Impacts (Assuming an Unchanged Rest of the World)

Change in Net Exports (Billions of 2008$)										
Discount rate	Exceedance Probability									Summary Risk
	99%	75%	50%	35%	25%	20%	10%	5%	1%	
0.0%	$21.5	-$1.6	-$20.6	-$33.7	-$44.7	-$51.5	-$71.0	-$88.9	-$126.6	-$25.2
1.5%	$16.9	$2.2	-$9.9	-$18.1	-$24.9	-$29.3	-$41.7	-$53.3	-$78.1	-$12.8
3.0%	$13.5	$3.8	-$4.1	-$9.3	-$13.7	-$16.5	-$24.6	-$32.4	-$49.3	-$6.0

Because climate change is predicted to increase the volatility of temperature and precipitation, the estimated impacts over time also show volatility. Figure 4-5 illustrates the annual impacts on the national GDP as a function of the exceedance probabilities of reduced precipitation noted in the legend of the graph. Years are highlighted here, unlike in the previous figures.

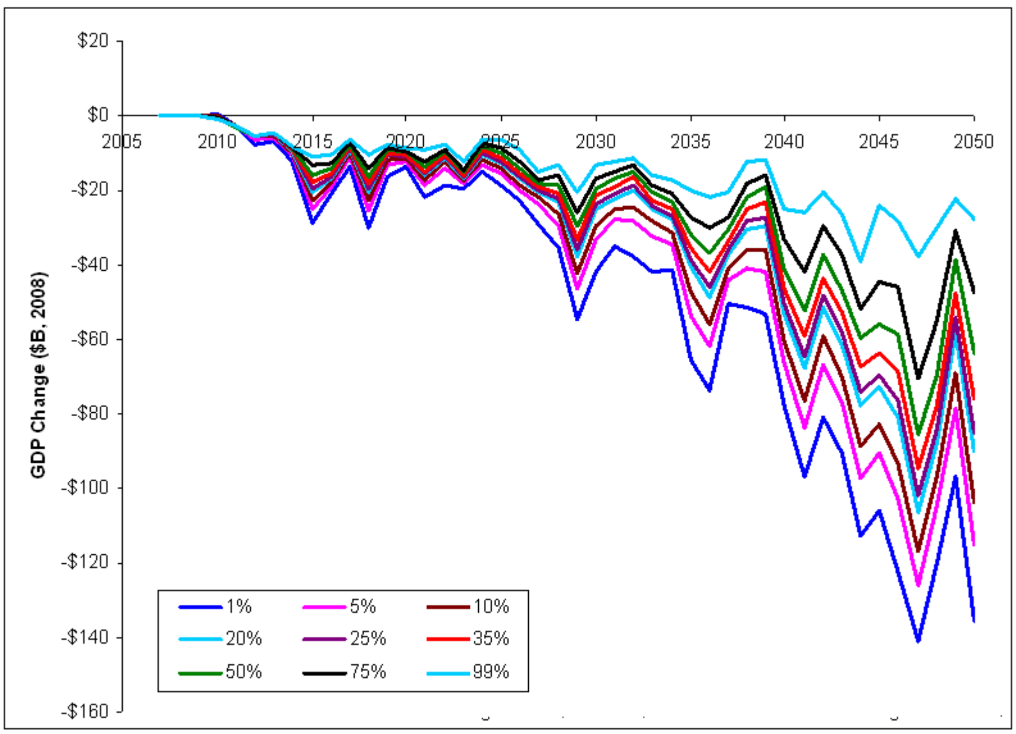

Figure 4-5. Annual U.S. GDP impacts from climate change.

As shown in Figure 4-5, greater losses are evident in succeeding years, and the lower exceedance probabilities are associated with greater impacts on the GDP. Examining the estimated impacts for 2015, the loss at the 99% exceedance probability is on the order of $10 billion per year, whereas at the 1% exceedance probability the loss is almost $30 billion per year. Note, however, that the same motif or pattern of volatility to represent the climate is used in all the simulations for these analyses. There is uncertainty in the variability just as there is in the long-term precipitation levels. Currently, available data do not allow a rigorous statistical inclusion of uncertainty in volatility within our analysis. Nonetheless, we can note that had a more changing and presumably increasingly volatile motif of year-by-year climatic conditions been used, the macroeconomic impacts would be larger and more problematic than the summary monetary impacts of this study indicate.

Table 4-4 presents our estimates of interpolated risks (that is, the probability-weighted consequence excluding those outside the range of 99% to 1% exceedance probabilities) by industry at the national level; the excluded estimates are between 1% and 0% and between 100% and 99%. Because of globalization, extreme probabilistic conditions cannot be properly represented in a U.S.-centric analysis, as we explicitly pursued in this study. Nonetheless, the difference between the summary risk calculated using only interpolated values and one also including extrapolated values would be different by a fractional amount. The results shown are presented in terms of contribution to the GDP. The impact on revenue would be larger, varying between less than 1.5 times larger for retail sales to more than 3.0 times larger for manufacturing. Due to construction, especially of power plants to augment lost hydroelectric capacity, utilities, electric equipment, and other manufacturing experience positive effects in terms of economic value. Transportation sees a net zero economic impact, despite an overall reduction in economic activity, because of the added need for interstate trade, especially for food. Although the reason is highly uncertain, the textile industry appears to see a net neutral impact due to the nonnegligible migration of population to the relatively colder northern states. Many professional services, including medical, see a drop because unemployment constrains additional spending. Agriculture-dependent industries encounter substantial declines.

Table 4-4. Sector-Specific Risk at the National Level (0% Discount Rate, Interpolated)

National-Level Industry Impacts 2010–2050 (0% Discount, Billions 2008$)				
Forestry and logging; Fishing, hunting	-$0.6		Water transportation	$0.0
Agriculture, forestry support activities; Other	-$0.3		Truck transportation, couriers	-$19.9
Oil and gas extraction	-$9.4		Transit and ground passenger transportation	-$0.6
Mining (except oil and gas)	-$86.3		Pipeline transportation	-$0.2
Support activities for mining	-$7.3		Tourist transportation; support activities	-$0.8
Utilities	$13.6		Warehousing and storage	-$2.1
Construction	-$30.8		Publishing industries, except Internet	-$12.4
Wood product manufacturing	-$1.1		Motion picture and sound recording industries	-$4.5
Nonmetallic mineral product manufacturing	-$3.3		Internet publishing, Information services	-$10.8
Primary metal manufacturing	-$2.4		Broadcasting, Telecommunications	-$28.1
Fabricated metal product manufacturing	-$3.7		Monetary authorities, funds, trusts, financials	-$34.1
Machinery manufacturing	-$4.2		Securities, commodity contracts, investments	-$39.9
Computer and electronic product mfg.	-$10.3		Insurance carriers and related activities	-$6.4
Electrical equipment and appliance mfg.	$1.4		Real estate	-$38.2
Motor vehicles, bodies & trailers, parts mfg.	-$8.8		Rental and leasing services	-$8.4
Other transportation equipment manufacturing	-$1.6		Professional and technical services	-$41.4
Furniture and related product manufacturing	-$3.6		Management of companies and enterprises	-$13.9
Miscellaneous manufacturing	$1.4		Administrative and support services	-$21.2
Food manufacturing	-$82.3		Waste management and remediation services	-$0.5
Beverage and tobacco product manufacturing	-$29.4		Educational services	-$2.2
Textile mills	$0.0		Ambulatory health care services	-$66.8
Textile product mills	-$1.0		Hospitals	-$5.5
Apparel manufacturing	$0.8		Nursing and residential care facilities	-$2.0
Leather and allied product manufacturing	-$2.3		Social assistance	-$2.0
Paper manufacturing	-$2.5		Performing arts and spectator sports	-$2.0
Printing and related support activities	-$0.6		Museums, historical sites, zoos, and parks	-$0.2
Petroleum and coal product manufacturing	-$3.6		Amusement, gambling, and recreation	-$5.9
Chemical manufacturing	-$18.2		Accommodation	-$3.8
Plastics and rubber product manufacturing	-$4.5		Food services and drinking places	-$19.9
Wholesale trade	-$45.3		Repair and maintenance	-$4.9
Retail trade	-$127.2		Personal and laundry services	-$11.2
Air transportation	-$4.1		Membership associations and organizations	-$2.0
Rail transportation	-$3.2		Private households	-$1.0

Table 4-5 presents an indication of the average percentage loss to the economy over our 40-year-analysis time frame. The results in Table 4-5 are strongly affected by rapidly escalating costs in outlying years (Hope 2006). The year-2050 percent impacts (not shown in the table) are typically 50% higher than the average over the 40-year period. The table also distinguishes the agricultural impacts from the nonagricultural impacts on the economy, and it adds an estimate of the impacts of personal disposable income. Although these economic impacts are a small fraction of the overall economic activity of the period, by 2050 they exceed $100 billion per year.

Table 4-5. Change in Labor Years, GDP, and Disposable Personal Income in $ and % Difference over the Referent Case: 2010–2050 (0% Discount Rate)

Run	Labor Years (k)		U.S. GDP (no crops)		U.S. GDP (from crops)[10]		Real Disposable Personal Income	
1%	-12,961	-0.15%	-$1,899	-0.16%	-$159	-0.01%	-$1,727	-0.19%
5%	-10,819	-0.12%	-$1,583	-0.13%	-$152	-0.01%	-$1,494	-0.16%
10%	-9,764	-0.11%	-$1,426	-0.12%	-$148	-0.01%	-$1,376	-0.15%
20%	-8,587	-0.10%	-$1,247	-0.10%	-$144	-0.01%	-$1,241	-0.14%
25%	-8,166	-0.09%	-$1,183	-0.10%	-$142	-0.01%	-$1,193	-0.13%
35%	-7,468	-0.08%	-$1,076	-0.09%	-$138	-0.01%	-$1,113	-0.12%
50%	-6,601	-0.07%	-$943	-0.08%	-$134	-0.01%	-$1,011	-0.11%

As presented in Table 4-5, decreases in labor years range from a loss of 13 million in the least probable simulation (1% exceedance probability) to about 6.6 million in the median simulation (50% exceedance probability). GDP losses range from about $1.9 trillion to about $0.9 trillion. GDP losses due to crops are relatively small, ranging from $0.16 trillion to $0.13 trillion. As we describe below in the sectorial analysis in Section 4.2, GDP losses for the downstream industries that use crops are much greater than direct agricultural losses. Losses in real disposable personal income range from about $1.7 trillion to $1.0 trillion. Losses in the median climate-change simulation remain substantial, with economic impacts about half as large as the lowest-probability simulation.

Figures 4-6 through 4-9 examine the dynamics of employment, personal disposable income, crop production, and industrial GDP contributions, respectively. The paths of these four items are highly erratic, reflecting the high volatility of the year-to-year forecasts of the climate conditions. During all years except 2010—where impacts are nearly zero—impacts as a function of reduced exceedance probability are monotonic, becoming worse in simulations predicting greater drought severity. The 2010 values show one particularly interesting insight of our analysis. The initial response of investment and construction for adapting to climate change has a positive impact on the economy. But this benefit is eventually overwhelmed by the impacts of climate change that the investments are attempting to counter. The magnitude of impacts for all items increases as time passes. As a result, if a discount rate greater than zero was applied to the net economic effects in Table 4-5, the magnitude of these impacts would be substantially reduced. A larger discount rate would dramatically reduce the present value of the most severe economic impacts—which occur 40 years into the future.

The legend in Figures 4-6 through 4-9, like the legend in Figure 4-5, refers to the estimated exceedance probability of reduced precipitation and subsequent reduced water availability. Because climate-change predictions show increased volatility of temperature

[10] This calculation assumes that changes in soy and corn production can be used as proxies for total crop production and uses a ratio of 0.801 of change in the GDP directly due to changes in crop production to corn and soy production. See Appendix B for the derivation of this ratio.

and precipitation, the impacts over time are far from smooth. Even though the lower-exceedance-probability simulations do reflect worsening conditions over time, note again that the motif for the climate remains a constant across the simulations.

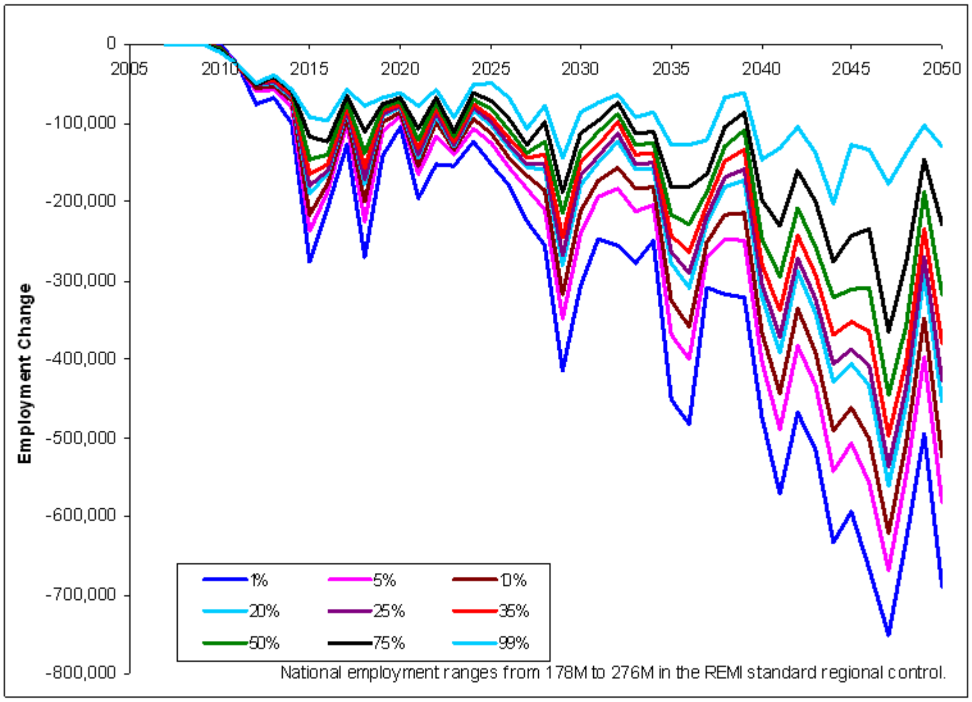

Figure 4-6. National employment impacts: 2010–2050.

The employment volatility depicted in Figure 4-6 shows a pattern similar to that for the GDP in Figure 4-5 shown previously, although the figures are somewhat different because of diversity in employment per level of output across different industries. That is, even if all industries were affected in the same way, labor-intensive industries would have a greater impact on unemployment than highly automated industries with few employees.

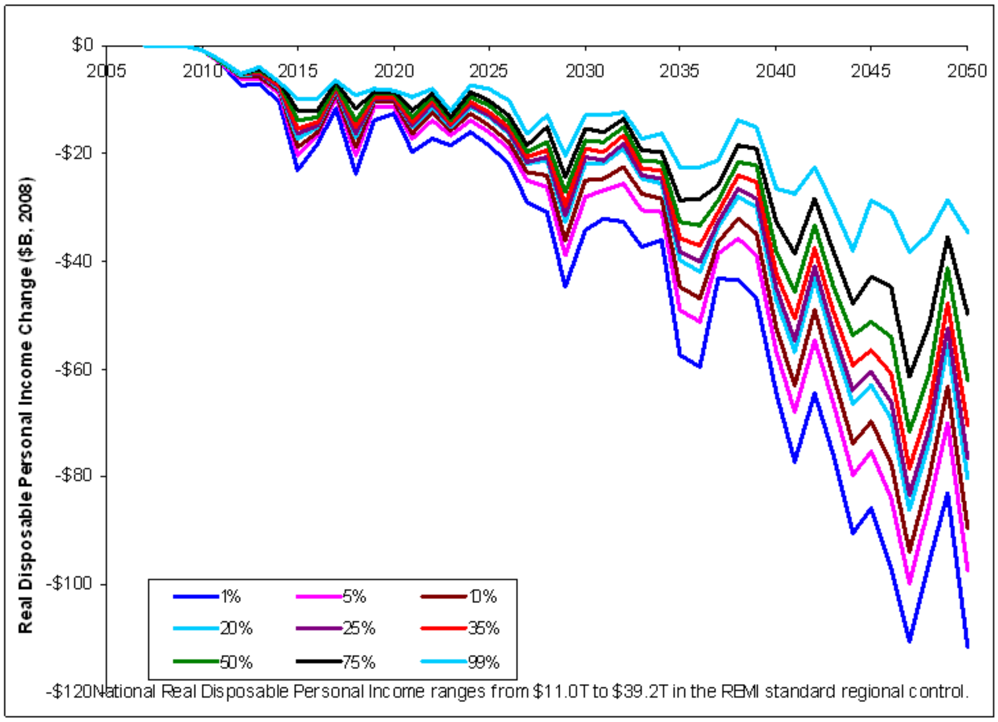

Figure 4-7. Change in national disposable personal Income (2008 USD): 2010–2050.

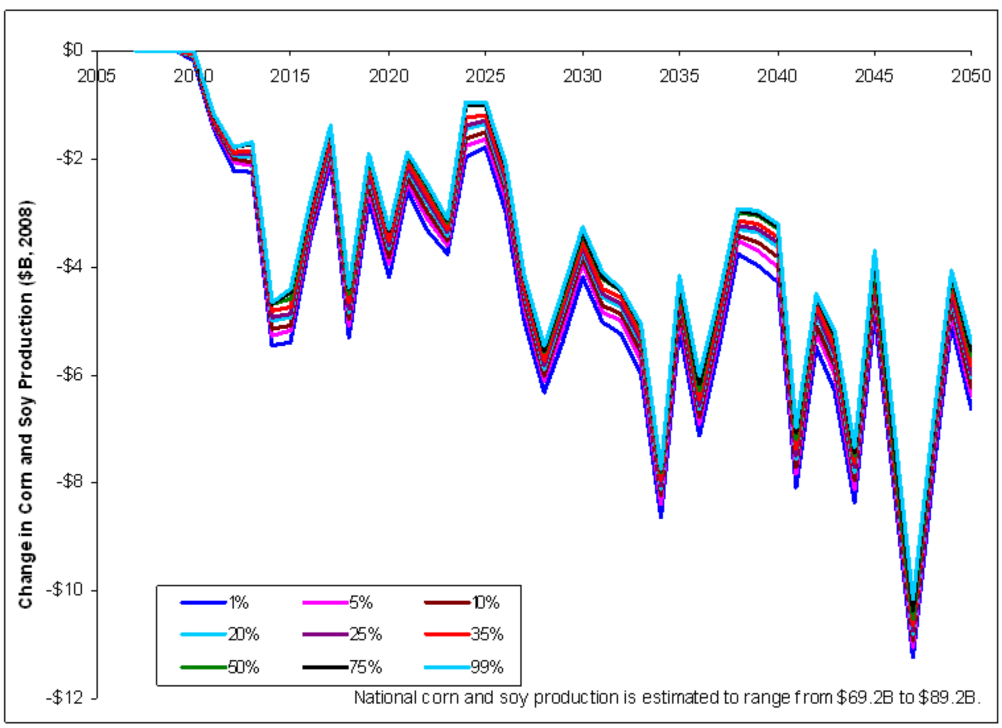

Figure 4-8. Change in crop production (corn and soy) (2008 USD): 2010–2050.

The change in crop production shown above in Figure 4-8 is influenced more by variation in the frequency and intensity of both temperature rise and precipitation fluctuations than by the average level of precipitation. The motif is constant among all the simulations, and therefore only precipitation levels cause the differences between simulations. The frequency and intensity of the temperature fluctuations, not precipitation, are predominantly responsible for the up-and-down nature and closeness of the impact lines observed in Figure 4-8.

Figure 4-9 shows the industries that lose the most GDP due to drought in the most severe simulation (the 1% exceedance-probability simulation).

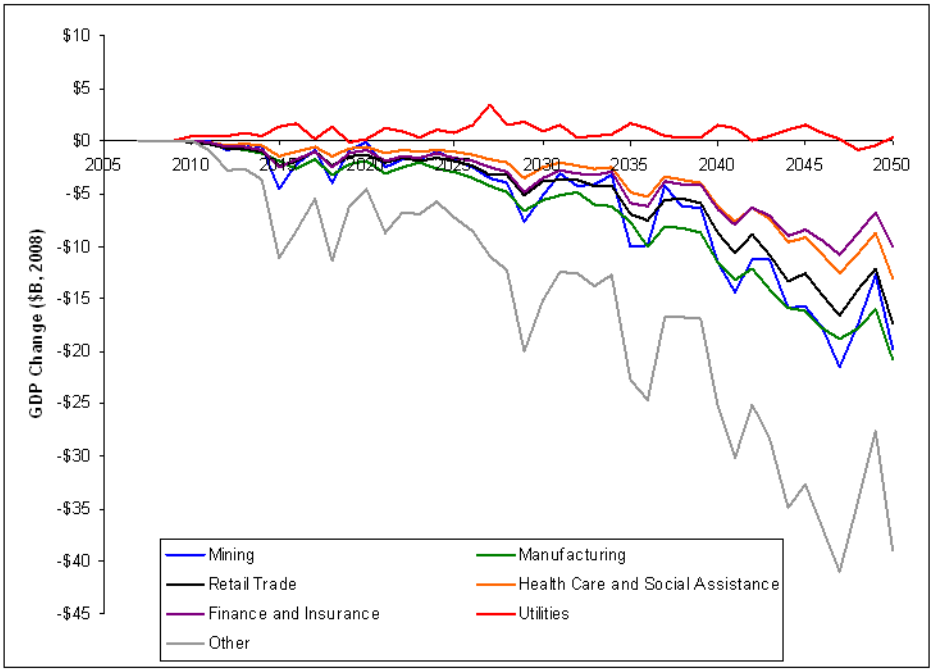

Figure 4-9. Changes in national GDP contributions by private, nonfarm sectors (2008 USD, 1% simulation): 2010–2050.

As seen in Figure 4-9, mining and manufacturing both have the largest losses of any economic sector, although the losses are relatively more severe in mining because mining is forecast to be a much smaller fraction of the economy.[11] Mining has the greatest losses due to the shutdowns in its operations as a result of a lack of consumptive water availability. Mining is particularly vulnerable to water shortages (Morrison et al. 2009). Other large losses occur in retail trade, health care and social assistance, and finance and insurance, which are consumer-oriented sectors that suffer from overall losses of jobs and income. The only sector predicted to undergo positive economic effects is the utilities sector. These gains are mainly the result of increases in economic activity (e.g., construction of new power plants and labor for those facilities) in this sector to

[11] In 2050, REMI's forecast GDP in its standard regional control is $6.8 trillion for manufacturing and $111 billion for mining, which reflects REMI's forecast that manufacturing will grow about 340% between 2007 and 2050, while mining will remain nearly constant.

compensate for net losses in hydroelectric production. New power plants (and labor for those facilities) in this sector compensate for net losses in hydroelectric production.

4.2 Sectorial Impacts

This section explores the relative contributions of subcategories of impacts, based on five categories of input variables into the REMI model: (1) impacts to farms, (2). impacts to industries that use farm output, (3) thermoelectric production, (4) hydroelectric power, and (5) industry and mining in separate REMI simulations. Additionally, the industry and mining impact category is assessed for a subcategory of variables without shutdowns for mining. A factor analysis explores how the consideration of different characterizations (factors) of the input to the economic model affects results.[12] All factor analysis simulations use the most-extreme global-climate-change simulation that forecasts droughts that have a 1% chance of being exceeded in magnitude.

The goal of the factor analysis presented here is to understand the relative contributions of different sets of input assumptions to aggregate-impact results. The factor analysis was conducted using results from the hydrological assessment and its determination of water availability. The hydrological simulation allocates water shortages so that each sector absorbs a percentage of the water deficit that is equal to that sector's water demand in relation to the total demand.

The REMI model produces hundreds of output variables. Our analysis concentrates on three of those variables: employment, GDP (a measure of the total economic value added to the economy from economic activity), and real disposable personal income (income adjusted for taxes and changes in price levels). For each variable, two graphs are presented. The first graph includes the first four categories of input variables (farms, farm industry, thermoelectric, and hydroelectric) to the model; the second graph includes two variants of the fourth category (industry and mining). These variants are (1) a full simulation and (2) a simulation without shutdowns in the mining industry. This split was chosen because the input variables affecting industry produce much larger economic consequences than the other categories and because the mining shutdown variables (i.e., reductions in "Industry Sales / Production") have especially large effects.

Graphs of these output variables are presented in Figure 4-10 through Figure 4-13. In addition, the total changes from 2010 through 2050 are presented in Table 4-6, and the biggest percentage changes to U.S. states are shown in Table 4-7, which is discussed further in this section. These figures and tables show that the economic impacts on the variables describing farming are generally positive but have the smallest magnitude. This minor economic impact is largely due to the changes toward more labor-intensive components of farming as crop production declines and farm prices rise. The farming industries support farming (with such items as fertilizer and tractors), and they experience magnified reductions in demand with reduced agricultural production.

[12] Note the term "factor" as used here denotes a factor of production, such as labor, and is not meant to construe a factor analysis in the statistical sense.

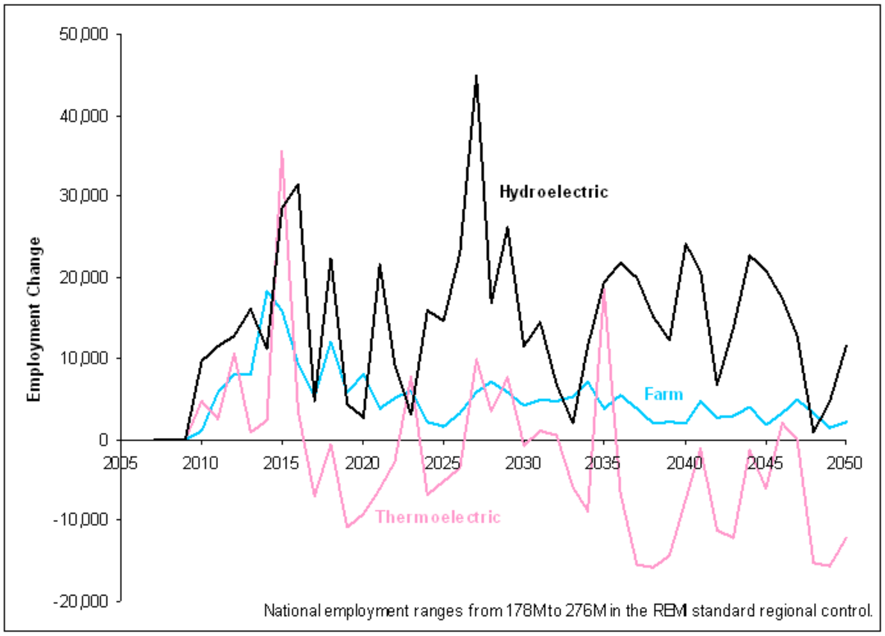

Figure 4-10. National employment impacts of farming, thermoelectric, and hydropower changes.

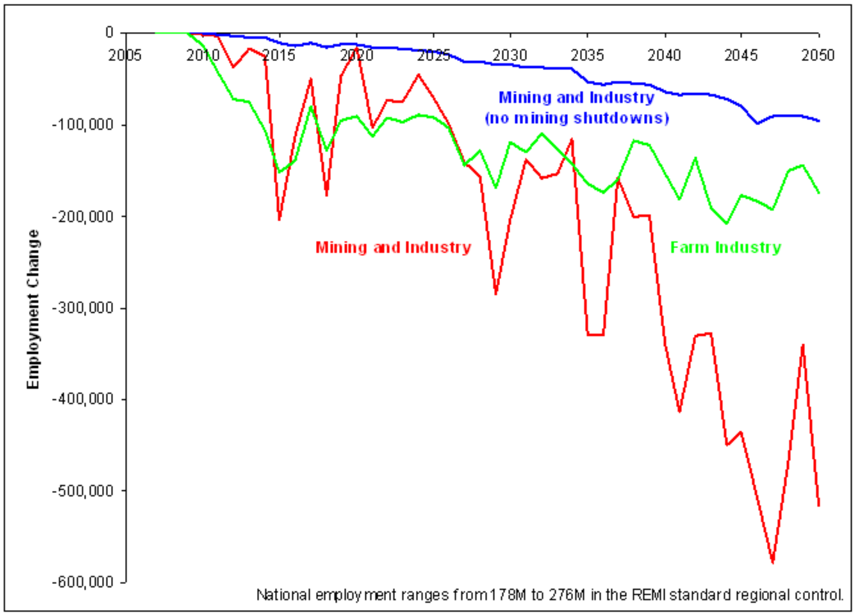

Figure 4-11. National employment impacts of farm-support industry, mining and industry.

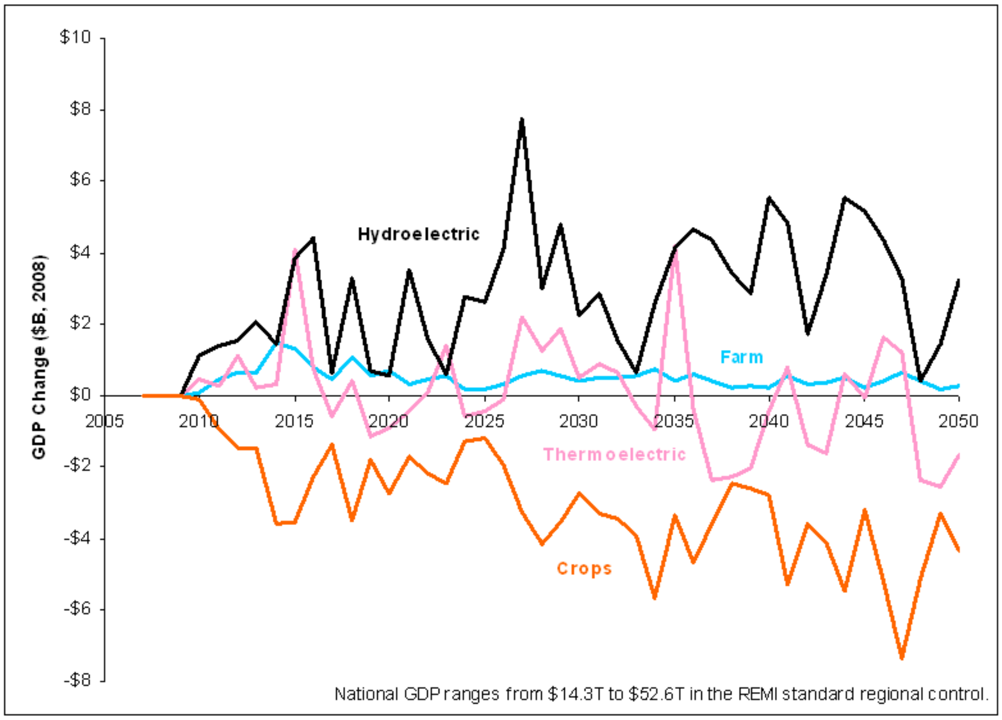

Figure 4-12. Change in national GDP (2008 USD), using farm, thermoelectric, and hydroelectric changes: 2010–2050.

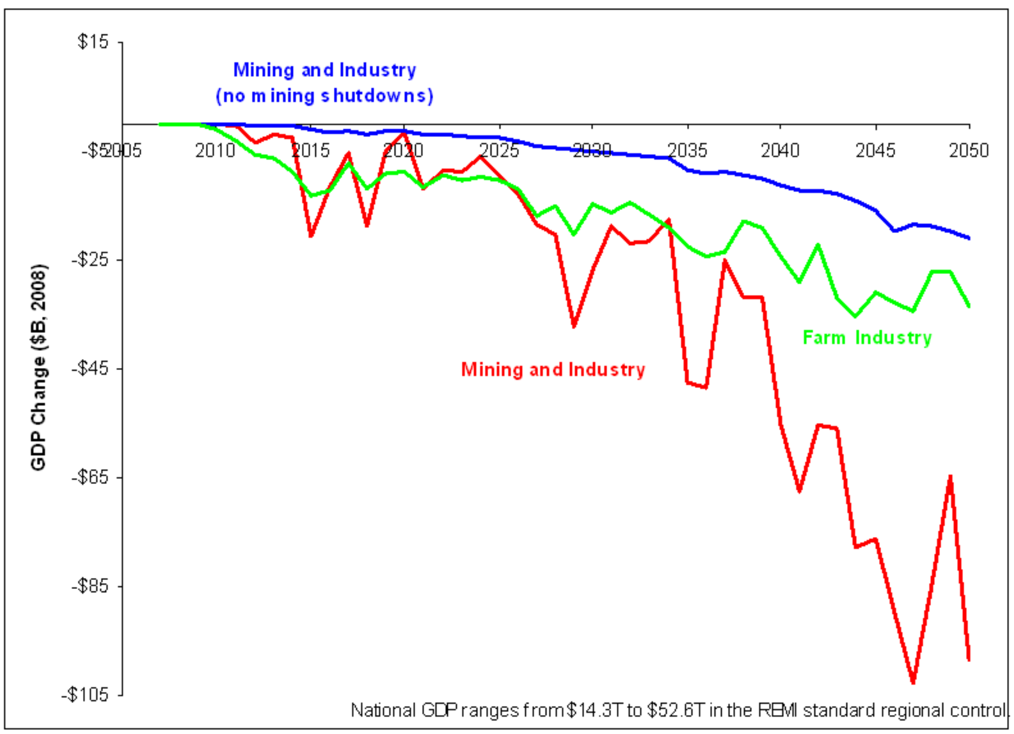

Figure 4-13. Change in national GDP (2008 USD), farm industry, mining and industry inputs: 2010–2050.

Table 4-6. Change in Labor Years, GDP, and Disposable Personal Income: 2010–2050

Category	Employment		U.S. GDP		Disposable Income	
1. Farm	216	0.0024%	$21B	0.0017%	$11B	0.0012%
2. Farm-Demanding Ind.	-5,286	-0.0594%	-$719B	-0.0598%	-$887B	-0.0976%
3. Thermoelectric	-91	-0.0010%	$2B	0.0002%	-$155B	-0.0170%
4. Hydroelectric	622	0.0070%	$120B	0.0100%	$47B	0.0052%
5. Industry and Mining	-8,428	-0.0946%	-$1,324B	-0.1101%	-$746B	-0.0820%
-Not including shutdowns	-1,641	-0.0184%	-$285B	-0.0237%	-$197B	-0.0217%

The thermoelectric input variables produce economic consequences of greater magnitude than the farm input variables and of slightly smaller magnitude than the hydroelectric variables. The thermoelectric input variables contain information on retrofit activity to compensate for reduced water availability. Positive spikes in the GDP and employment occasionally appear in Figures 4-12 and 4-13, presented previously, especially earlier in time when investments in retrofit technologies first begin. However, these increases are often more than compensated for by the negative effects of increasing electricity generation costs in later years. The increases in electricity costs affect the production costs of other industries, causing an increase in the price index (inflation) throughout time, resulting in a steadily decreasing trend of real disposable personal income and reaching an annual loss of over $8 billion by 2050. Despite the net decrease of real disposable personal income of $155 billion during this period, there is a slight net increase in the GDP of $2 billion. However, that difference is due to investments in cooling retrofits that mitigate water shortages. If those retrofits were unnecessary, additional economic resources would be available for more productive use.

The only economic impacts that are positive overall are due to reductions in hydroelectric power production. Reductions in hydroelectric power increase the demand for alternate sources of power from the utilities sector (as described further in Appendix B). This increased demand causes increases in economic activity in electric utilities as power plants are built, workers are hired to work in those plants, and fuel is purchased to power the plants, while the hydroelectric plants continue to operate with essentially the same labor and costs but with reduced output. The increases in economic activity highlight a problem—most familiar to economists who analyze disasters—with using aggregate measures of economic flows for consequence analysis: the lost service of hydroelectric power production is not measured in these economic flows, but the increased economic activity necessary to compensate for these losses is measured. If hydroelectric power production did not decrease, the economic resources utilized to create power from alternate sources could be used for other means (such as building luxury items) that would improve the demand for other goods and services.

The input variables for the farm industry have the second highest change in employment and GDP, and the greatest impact on real disposable personal income. The annual loss in the GDP due to the sector hovers around $30 billion in the later years of the simulation, while the annual loss in real disposable personal income reaches $40 billion.

The mining and industry impact shows a much greater change than the other categories of impacts, with the exception that the magnitude of the losses to real disposable personal income are slightly less than they are for the farm industry. The maximum loss in the annual GDP is about $103 billion, whereas the maximum annual loss in any of the other three categories is about $35 billion (for the farm industry). Partial and total shutdowns of mining and industry have a substantial negative effect on the economic output and are largely responsible for the substantial volatility of the economic output—when no shutdowns are included in the REMI simulation, all of the economic output variables (see Figure 4-14) decrease relatively smoothly. Because of the water allocation scheme, water availability to high-value industry never falls enough to cause industry shutdowns, thus shutdowns only affect mining through 2050. From the perspective of an individual mining operation, the sale of water rights may represent a profitable option.

Reductions in water availability to mining cause relatively severe economic consequences because mining typically uses water efficiently. As discussed in Appendix B, there are few opportunities for conservation without shutting down mining activity in states that are not adjacent to the ocean. All of the industries use a much greater share of their water for cooling, so they can conserve much greater portions of their consumption. Additionally, all of the industries simulated in the REMI model are represented as an aggregate, so no industry begins shutting down production until all industries have made all possible cooling retrofits, thus raising the fraction of water that can be conserved through cooling retrofits.[13] Because large municipal water suppliers serve most of industry, this aggregate view of a shutdown threshold is probably realistic. Figure 4-14 shows that under extreme drought at the 1% exceedance probability, water demand from municipal and high-value-added industries (with consequent demands for electric power) reduces agriculture and mining water availability to a large extent (by a factor of 2 to 1 for the water allocation logic used in this analysis). The difference between the mining curve with and without shutdowns indicates the extent to which the unavailability of water to sustain operations affects the magnitude of total economic loss.

[13] The smallest value of $\overline{\%c_t^i}$, which is the percentage of industrial consumption that can be conserved by retrofitting cooling in states not adjacent to an ocean (see Appendix B, Section B.5), is 32.4%. The median is 41.0%. For mining, on the other hand, the value of the term is always 6%.

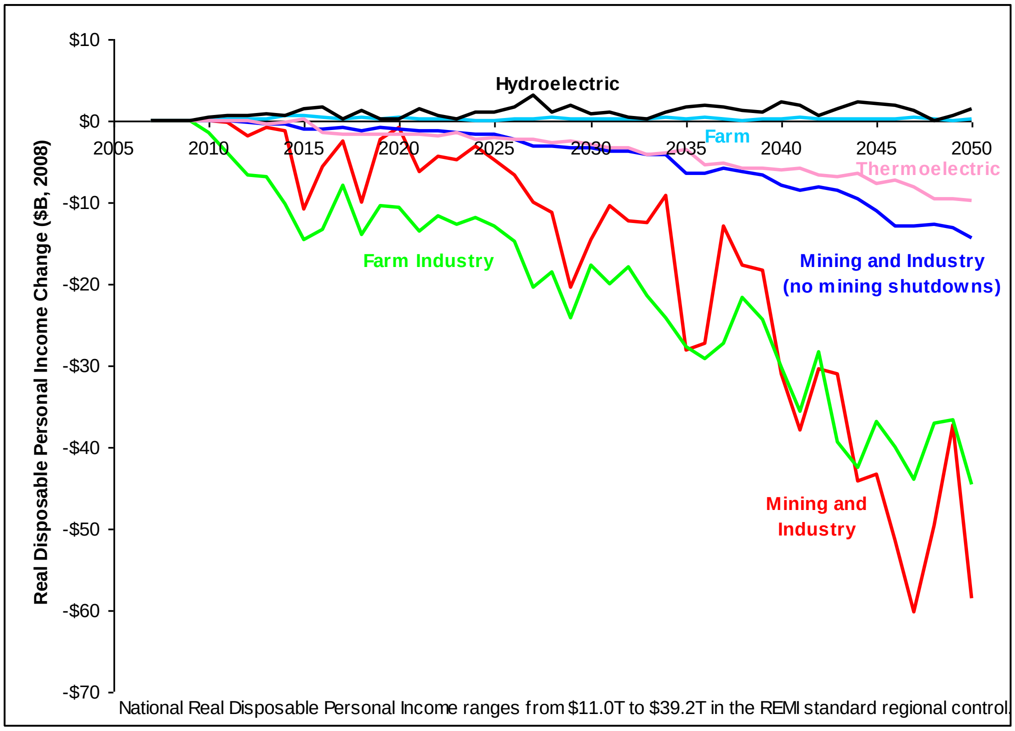

Figure 4-14. Change in national real disposable personal income (2008 USD), using farm, farm industry, thermoelectric, hydroelectric, and mining and industry inputs.

Table 4-7 lists the states with the largest percentages of gains and losses in 2050 in population and real disposable personal income (both variables were chosen because they change with a clear trend and are measures of socioeconomic dislocation). The relative magnitudes of the largest state-level changes in the different simulations are similar to the magnitudes of the national-level value.

Table 4-7. States with Largest Percentage Changes in Population and Income: 2050

Category	Population		Disposable Income	
Largest Loss (Smallest Gain)				
1. Farm	0.00%	WY	0.00%	WY
2. Farm-Demanding Industries	-0.24%	GA	-0.38%	GA
3. Thermoelectric	-0.10%	WV	-0.15%	WV
4. Hydroelectric	-0.01%	MD	0.00%	IL
5. Industry and Mining	-3.41%	WV	-4.11%	WV
-Not including mining shutdowns	-0.05%	IA	-0.09%	IA
Largest Gain (Smallest Loss)				
1. Farm	0.02%	NE	0.02%	NE
2. Farm-Demanding Industries	0.26%	OR	0.16%	OR
3. Thermoelectric	0.02%	DE	0.00%	DE
4. Hydroelectric	0.02%	AZ	0.03%	AZ
5. Industry and Mining	0.13%	OR	0.01%	OR
-Not including mining shutdowns	0.02%	OR	-0.01%	

The largest economic losses are to West Virginia in the simulation that includes shutdowns of the mining industry. In this simulation, West Virginia loses 3.41% of its projected population and 4.11% of its projected real disposable personal income by 2050. This result is expected because a large fraction (8% of output[14]) of the West Virginia economy is mining; and according to the defined water allocation scheme, mining experiences twice the proportional reduction in water availability than the higher-value-added industries.

For many of the categories of variables, the largest gains and losses for population and real disposable personal income are in states with large populations. For example, for the industry and mining category, California gains more than 58,200 residents by 2050, which is over twice as large as the second greatest increase (Florida, with a gain of about 27,500 residents). Based on the percentage gain compared with the baseline, however, California has the eighth largest gain (an increase of 0.10%). These gains in population occur despite large losses in the GDP ($3.9 billion) and real disposable personal income ($1.2 billion). Some states fare relatively worse compared with other states, and their residents choose to relocate. California, as the most populous state in the nation, is a likely destination of those emigrants. It also maintains a comparative economic advantage relative to other states in dealing with the impacts of climate change in the long term despite significant negative impacts in the short term. The concept of comparative advantage affects many of the state-level results of this study and has a long history in the field of economics (Ricardo 1817).

[14] In REMI's standard regional-control simulation, West Virginia's total output in 2050 is $203 billion, and its total output in mining is $16 billion.

4.3 The Impact of Interannum Volatility

We now present an additional analysis that was conducted using inputs to the electricity production sector to explore how the volatility of the data (i.e., the motif as discussed in the introduction to Section 2 and in Section 3.1.2) affects the average estimated macroeconomic impacts. The results from the 1% exceedance-probability simulation using the year-to-year water-availability forecasts are compared with a simulation created by linearly changing water availability to electricity production between 100% and the minimum of the 2010 to 2050 values for each state. The water-availability forecast uses the same 1% exceedance-probability data used in the previous section—the most extreme reduction in precipitation, with a 1% chance of its severity being exceeded. Many climate-impact studies assume a gradual change in climatic conditions or base their analysis on a snapshot of expected conditions in future years. These approaches neglect the volatility we explicitly address in this analysis. Volatility results show dramatic changes over time and provide policy makers a better roadmap for responding sooner to potential events than is available from linear, or smoothed, results.

Figure 4-15 shows the difference in national employment between the simulations and the macroeconomic referent using the Sandia hydrological model's simulated (volatile) water availability and using an, on average, equivalent downward linear trend over time. The thermoelectric designation in the figure just means that the water availability used is that for the thermoelectric, municipal, and industrial sectors. The forecasts of water availability show a high degree of variability. Employment varies with increases of more than 35,000 jobs in 2015, while decreases nearly reach a loss of 16,000 jobs in later years. When the simulation is conducted using a downward linear trend, increases in employment initially spike above 9,000 in 2010 but then return to a roughly steady decrease of around 1,000 jobs per year.

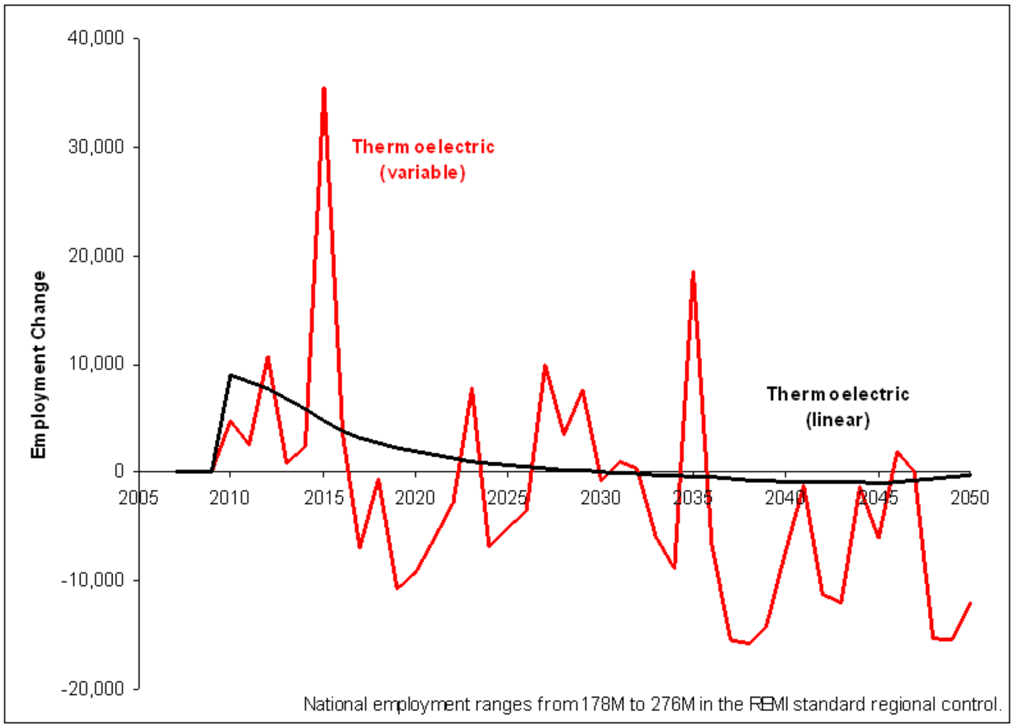

Figure 4-15. Change in national employment, using simulated thermoelectric sector water-availability data: 2010–2050.

Figure 4-16 shows the annual change in the GDP for the same simulations. The pattern is similar to the change in employment, except the magnitude of the GDP changes becomes slightly larger in the second half of the simulation for both the variable data and the linear data.

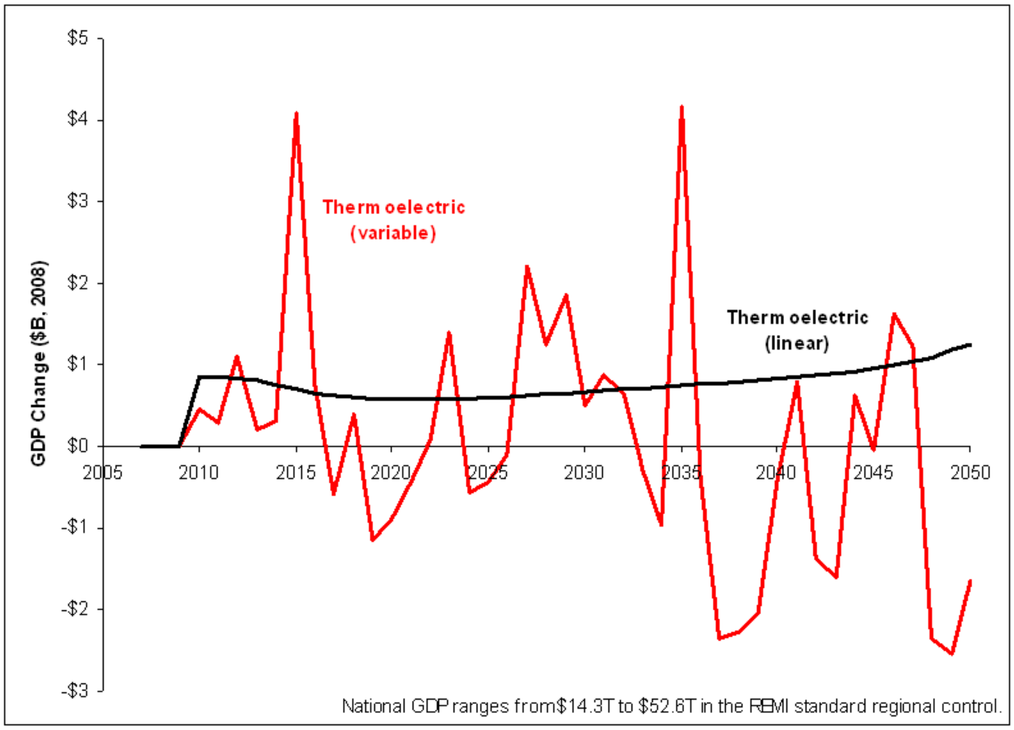

Figure 4-16. Change in national GDP (2008 USD), using simulated thermoelectric sector water-availability data: 2010–2050/

Figure 4-17 shows changes in real disposable personal income for the same simulations. Although the simulation using the forecasted water availability continues to exhibit greater volatility than the simulation using the linear trend, it is less variable than the time series of employment or the GDP in Figures 4-15 and 4-16 generated from the water-availability forecasts.

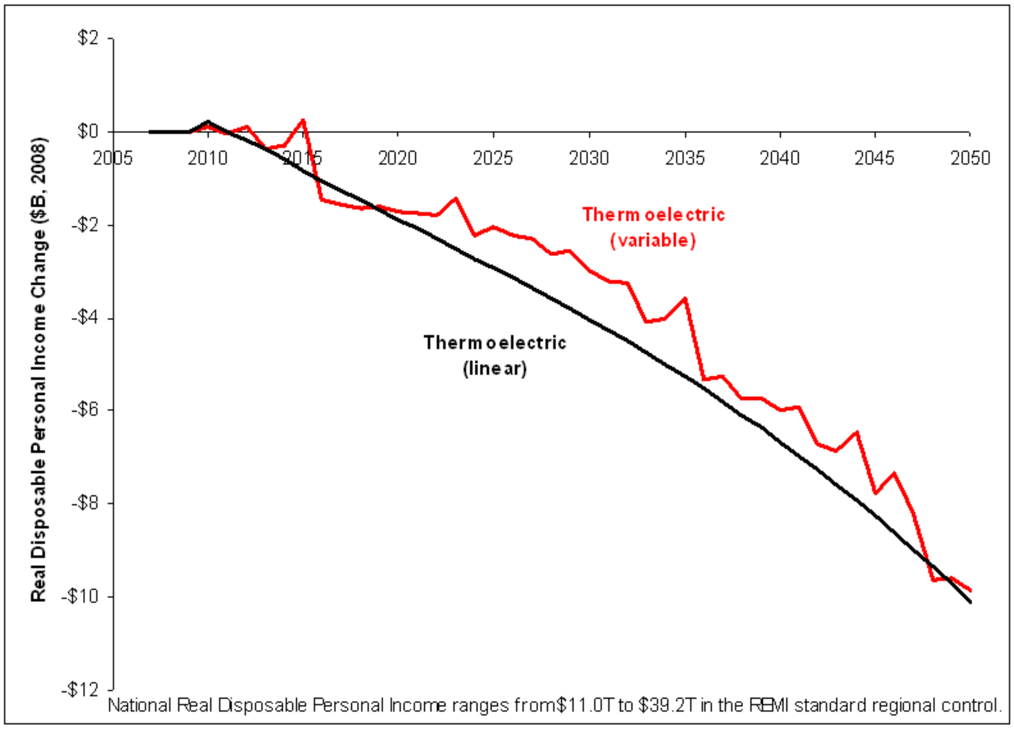

Figure 4-17. Change in national real disposable personal income (2008 USD), using simulated thermoelectric sector water-availability data: 2010–2050.

Real disposable personal income is driven by changes in commodity prices, which are affected by increases in production costs. These changes in the price level accumulate gradually over time, leading to a steady decrease in real disposable personal income as seen above in Figure 4-17. The volatility of the water availability means that the GDP fluctuates from year to year, resulting in slight fluctuations of the variable forecast from the linear forecast. Furthermore, the variable forecast has slightly higher losses than the linear forecast because the GDP in the variable forecast remains higher (smaller losses) than it is in the linear forecast in the earlier years of the simulation.

In summary, the results of these simulations suggest that the economic consequences of variable global climate change may cause more substantial year-to-year disruptions than climate change would cause if it followed a smooth linear trend. Hallegate et al. (2007) explore this issue more thoroughly. Additionally, the economic methodology (which assumes that firms make permanent retrofits to mitigate reductions in water availability) and the logic of the REMI model cause the simulations that include volatility to have permanently lower levels of real disposable personal income.

4.4 State Impacts

The national-level results show that economic impacts for the entire nation are negative. However, this aggregate look at the economic impacts of drought induced by climate change may ignore important regional differences that create disproportional positive and negative impacts across regions. Examining regional differences is particularly pertinent for this analysis because drought caused by climate change will vary in severity across the United States and different regions of the country contain different mixes of industry that will suffer to different extents from drought. For example, heavy consumers of water tend to cluster together near sources of water, thus there is little water-intensive industry in most western, arid states.

Table 4-8 shows the estimated national- and state-level risk to the GDP, employment, and interstate population migration. The values are the sum of the probability-weighted impacts over the exceedance probabilities and over the 2010 to 2050 period. The migration across states is often based on comparative advantage. Even if a given state economy is having difficulties, it may be having less difficulty than other states. If we look at the state of New York, we see that the summary impact of climate change from 2010 to 2050 is a loss of $122 billion with a 0% discount rate. This loss is reduced to $81 billion with a 1.5% discount rate and to $54 billion with a 3% discount rate. The drop is dramatic because much of the impact occurs in the later years. Note that the reduced economic activity does reduce employment by 560,000 labor years by 2050 even though the population has risen by 7,200 people due to in-migration from the even-more-affected surrounding states. This means that the unemployment in New York is increasing even more than the drop in economic activity would indicate.

Figure 4-18 through Figure 4-24 show maps of U.S. state-level impacts for the GDP, employment, population, and corn for the total risk and also for the 1% exceedance-probability (worst-case) conditions. The coloring scheme (green is good, yellow is neutral, and red is bad) used in these maps is based on the percentage impact relative to the state's size. The impact values providing the numerical population change are quantified in absolute units of measure. As an example, in Figure 4-23, which presents population changes for 2050 at a 1% exceedance probability, New Mexico is one of four states that lose more than a half-percent of their population and hence is colored red. For a state with a low population, a loss of 14,000 people is significant. Texas, on the other hand, loses around 11,600 people but is colored yellow because the percentage impact is small for a state with such a large population.

These maps show that all states suffer negative economic impacts for all variables, except for three states in the Northwest (Washington, Oregon, Idaho)—with Montana, California, and Colorado showing benefits for the summary risk but losses at the 1% exceedance probability. Washington, Oregon, and Idaho have only slightly positive impacts, but their slight gains are at the expense of other states because these three states experience the largest increases in population (Figure 4-20). Population migration in effect transfers economic activity from other states. The gains in these Northwest states are also due to the increases in demand for utilities that result from reduced hydroelectric power production. California, while predicted to suffer from the reduced precipitation in early years, is predicted to benefit economically from the later-year population movements. Colorado is predicted to prosper in the early years while there is still adequate water but experiences mounting losses in the later years as a result of reduced water. Montana is predicted to be the only state that (slightly) benefits from both adequate water and population migration. Predicted economic impacts are particularly severe in interior states where it is not economically viable to substitute to desalinated water and greatest in states like West Virginia with large concentrations of mining. For example, the GDP risk for West Virginia is estimated to be about 2.6% less than predicted without the consequences of reduced precipitation. That the U.S. Northeast and Southeast are susceptible to climate-induced water availability issues to the extent examined herein has been studied previously (Oxfam 2009; Mack, 2009).

Table 4-9 shows the state-level impacts at the 1% exceedance probability for comparison with the summary risk in Table 4-8. If we again look at New York, as we did for Table 4.8, we see that for the 1% exceedance-probability simulation, New York's summary risk is $157 billion. There is only a modest 30% increase in the 1% exceedance-probability value compared to the summary value. Note that for states like Colorado, the GDP impact reverses sign between the 1% exceedance-probability case ($34 billion loss) to the summary risk value ($1 billion benefit). In the 1% exceedance-probability simulation, New York loses nearly another 100,000 labor years compared to the summary risk value. The increase in population, however, is more than three times larger, going from 7,200 people for the summary risk value to 23,000 in the 1% exceedance-probability simulation.

Figure 4-20 shows a map of state-level population changes in 2050. Like the economic impacts, population impacts create a similar number of disproportional positive and negative impacts across the U.S. states. National population changes (changes in birth rates and death rates) due to climate are not part of this analysis, so regional population changes above those captured in the macroeconomic referent are entirely the result of Americans moving from one state to another for economic reasons. There is a strong regional pattern with states in the Southeast and Southwest losing population and states on the West Coast, the western Midwest, and the Northeast gaining. Once again, interior states with the greatest concentrations of mining, such as West Virginia and Wyoming, are most affected.

States that gain population may experience negative, nonmonetary impacts that are not modeled within this study. For example, all states adjacent to the Atlantic Coast in the Northeast are predicted to gain in population, but these states then become more susceptible to damage from presumed extreme weather associated with global climate change because of the increased population concentrations (Changnon 2003).

Figure 4-21 through Figure 4-24 show the 1% exceedance-probability impacts. These impacts are larger than the total risk reported in Figure 4-18 through Figure 4-20 but are comparable in most cases. For a few states, the analysis results are dramatically different because higher exceedance-probability (> 35%) impacts may actually show positive effects compared with the macroeconomic referent, such as in Colorado where analysis results indicate there would still be adequate water with a growing demand for goods from states that are negatively affected.

Figure 4-24 shows the predicted change in the value of corn and soy production across states at the 1% exceedance-probability. A strong regional pattern emerges with the largest percentage losses across all Southern, Southwest, and Eastern states. The Midwest, which produces the most corn and soy, experiences only minor losses while the

Northwest experiences gains. States with little or no crop impact do not have recorded corn and soy production. The 1% exceedance-probability impacts can differ in sign from the summary risk because the impacts can have different signs at different exceedance probabilities, especially in the central latitude states where precipitation goes from sufficient to insufficient as the exceedance probability decreases. Further, the comparative economic advantage among the states can shift when states negatively affected at high exceedance-probabilities relatively improve in the lower exceedance-probabilities as the neighboring states experience negative impacts.

Despite suffering greater drought conditions on average relative to the rest of the nation, California in this study shows improvements because its economic impacts are relatively less than those of other states. This comparative advantage occurs because some states have little flexibility in dealing with water shortages, for example, because there is little agricultural irrigation from which water can be diverted. In general, those states that already suffer water constraints (often due to irrigation loads combined with urban growth in arid regions) have processes in place to adjust to changes in water availability. Irrigation-water use may buffer fluctuating water shortages, assuming the viability of food imports. The value added to the national economy from certain types of industry is large compared to that for food production. Thus, the impact of reduced agriculture is partially compensated by the continued operation of high-value-added industry.

The estimated California case is particularly illuminating because these predictions are counterintuitive. In the early years of climate change the state suffers significantly from reduced precipitation and in the later years achieves comparative advantage. A review of California's current problems and future opportunities indicates support for the analysis results (Grunwald 2009). There are time-dependent dynamics among several states where the geographical movement of the precipitation conditions and the change in comparative advantage cause a reversal of cost and benefit from climate change over the 40 years. Similarly, high-exceedance-probability conditions may show benefits or losses that may be reversed with lower-exceedance-probability conditions.

Conversely, the Pacific Northwest states show improvement under climate change due to expected increased precipitation. This study is limited to the annual temporal resolution of precipitation levels (other than capturing monthly variation for agricultural assessments) and thus does not capture the impact from lost seasonal snowpack water-storage in the Pacific Northwest, which is an intra-annual process. Consequently, the estimated positive economic impacts could be an artifact of our assumptions in this study. On the other hand, people migrating to the Pacific Northwest from other states may provide positive economic impacts even if hydropower declines and there are added requirements for increasing local water storage.

As larger populations use a larger fraction of the existing water supplies, the Northeast and the Southeast experience negative impacts, even if the reductions in long-term precipitation are minimal. In general, a decreasing exceedance probability (from 50% to 1%) implies that reduced precipitation (i.e., drought) is moving north and east at a continental level, causing more-severe reductions in precipitation in areas that experience reduced precipitation at the larger exceedance probabilities (> 50%). Picture a horizontal line that begins across New Mexico and Texas and starts to sweep in a diagonal fashion as it moves north and east in the direction of Maine. Thus, areas such as Colorado go from having adequate water and benefits in high-exceedance-probability simulations to experiencing losses from reduced water availability in the low-exceedance-probability simulations. Other than in the Pacific Northwest, water availability decreases over time with climate change. The decrease in water availability may not be solely due to a change in the water supply as a consequence of reduced precipitation but due to a change in demand as a consequence of industry and population migrating into the state.

Table 4-8. National and State-Level Risk 2010–2050

Summary of Climate Impacts (2010-2050)

Region	Change in GDP (Billions of 2008$)			Change in Empl. (Thous. Labor-Years)	Change in Pop. (Thous. People)
	Discount Rates				
	0.0%	1.5%	3.0%		
United States	**-$1,204.8**	**-$790.3**	**-$534.5**	**-6,862.7**	**0.0**
Alabama	-$29.2	-$18.9	-$12.6	-246.1	-10.8
Arizona	-$69.0	-$45.8	-$31.2	-481.2	-14.8
Arkansas	-$11.9	-$7.6	-$5.0	-96.8	-2.4
California	$25.1	$16.6	$11.5	152.0	115.7
Colorado	$1.2	$0.4	$0.0	22.8	15.3
Connecticut	-$9.5	-$6.3	-$4.3	-36.4	4.7
Delaware	-$4.8	-$3.1	-$2.1	-30.3	0.0
D.C.	-$4.7	-$3.1	-$2.1	-15.5	0.5
Florida	-$146.3	-$97.5	-$66.9	-1,242.4	-55.5
Georgia	-$102.9	-$67.7	-$45.9	-752.6	-40.0
Idaho	$4.0	$2.5	$1.6	33.3	6.9
Illinois	-$10.1	-$5.1	-$2.5	-36.7	15.7
Indiana	-$21.8	-$12.9	-$7.8	-130.1	-4.0
Iowa	-$2.8	-$1.4	-$0.6	-10.3	3.1
Kansas	-$6.3	-$4.1	-$2.7	-43.5	2.3
Kentucky	-$40.6	-$24.9	-$15.6	-289.6	-21.6
Louisiana	-$14.3	-$9.4	-$6.3	-119.4	-0.9
Maine	-$0.3	-$0.2	-$0.2	-4.4	2.5
Maryland	-$23.7	-$15.6	-$10.5	-163.0	0.1
Massachusetts	-$9.0	-$5.9	-$4.1	-37.8	12.9
Michigan	-$18.3	-$11.2	-$7.1	-107.7	7.1
Minnesota	-$8.3	-$4.9	-$2.9	-36.8	7.6
Mississippi	-$7.3	-$4.7	-$3.1	-63.0	-0.8
Missouri	-$3.8	-$2.2	-$1.3	-22.7	8.3
Montana	$0.9	$0.6	$0.4	12.8	2.9
Nebraska	-$1.4	-$0.8	-$0.4	-4.4	2.5
Nevada	-$38.7	-$26.2	-$18.1	-220.6	-2.8
New Hampshire	-$1.8	-$1.2	-$0.8	-12.1	2.6
New Jersey	-$38.9	-$25.8	-$17.6	-205.9	3.6
New Mexico	-$26.1	-$17.9	-$12.7	-217.6	-8.3
New York	-$122.9	-$80.5	-$54.4	-560.4	7.2
North Carolina	-$63.4	-$41.6	-$28.1	-492.4	-19.8
North Dakota	-$0.9	-$0.5	-$0.3	-5.4	0.8
Ohio	-$26.7	-$16.1	-$10.0	-167.7	1.7
Oklahoma	-$38.0	-$25.2	-$17.2	-312.0	-15.3
Oregon	$19.4	$12.5	$8.3	152.7	20.5
Pennsylvania	-$64.6	-$42.4	-$28.7	-459.1	-7.7
Rhode Island	-$0.7	-$0.5	-$0.3	-3.2	1.8
South Carolina	-$24.2	-$15.9	-$10.7	-235.4	-10.2
South Dakota	-$0.5	-$0.3	-$0.2	-2.1	1.3
Tennessee	-$58.5	-$37.3	-$24.4	-440.0	-23.0
Texas	-$137.8	-$91.0	-$61.9	-1,045.9	-28.5
Utah	-$10.5	-$6.9	-$4.6	-72.2	2.2
Vermont	-$0.7	-$0.4	-$0.3	-5.5	1.0
Virginia	-$45.4	-$29.7	-$20.1	-314.2	-5.9
Washington	$26.6	$17.0	$11.2	190.7	29.5
West Virginia	-$45.9	-$27.7	-$17.0	-306.4	-34.5
Wisconsin	-$6.2	-$3.7	-$2.2	-38.8	6.6
Wyoming	-$3.0	-$1.9	-$1.3	-19.2	-0.5

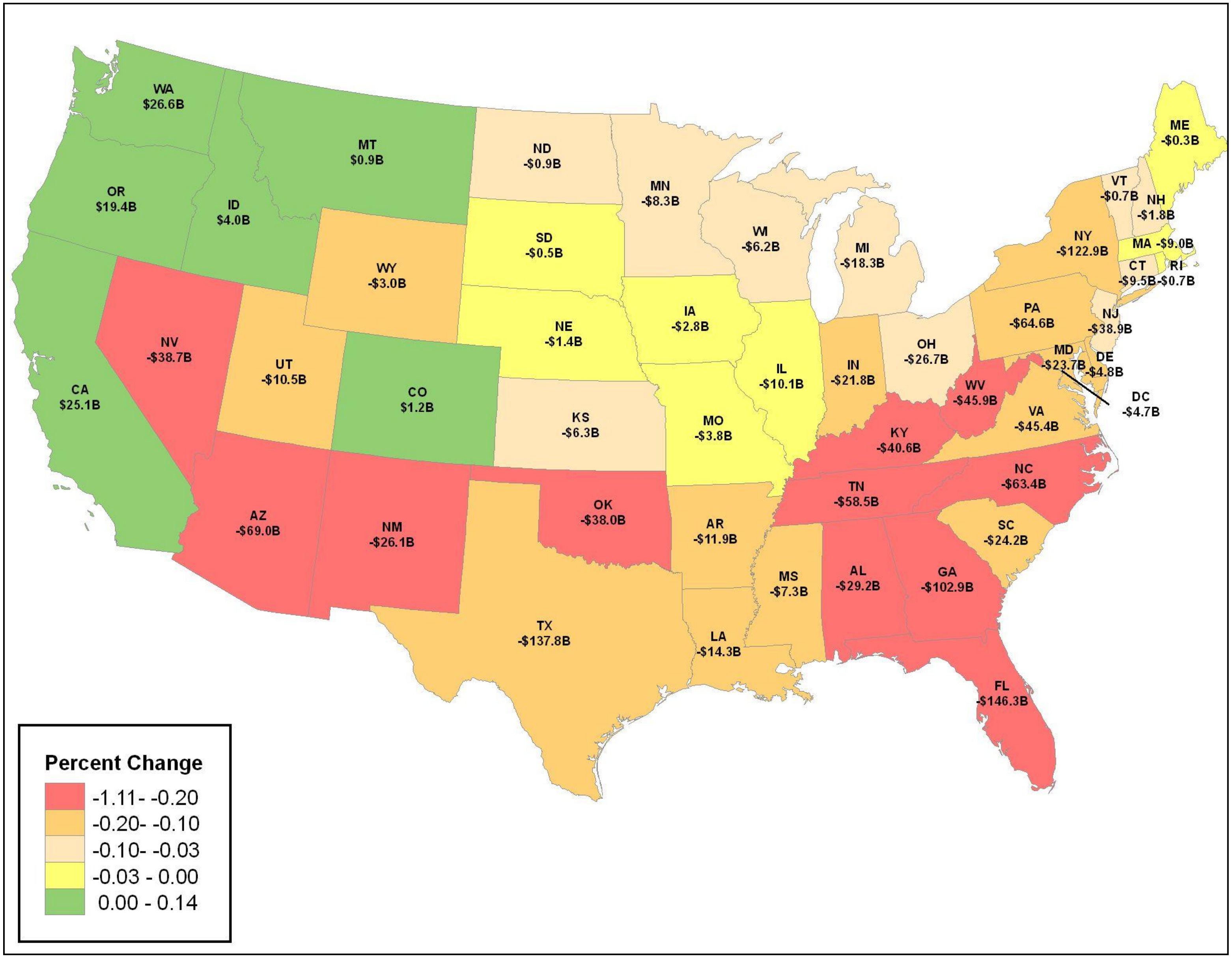

Figure 4-18. GDP risk 0% discount**.**

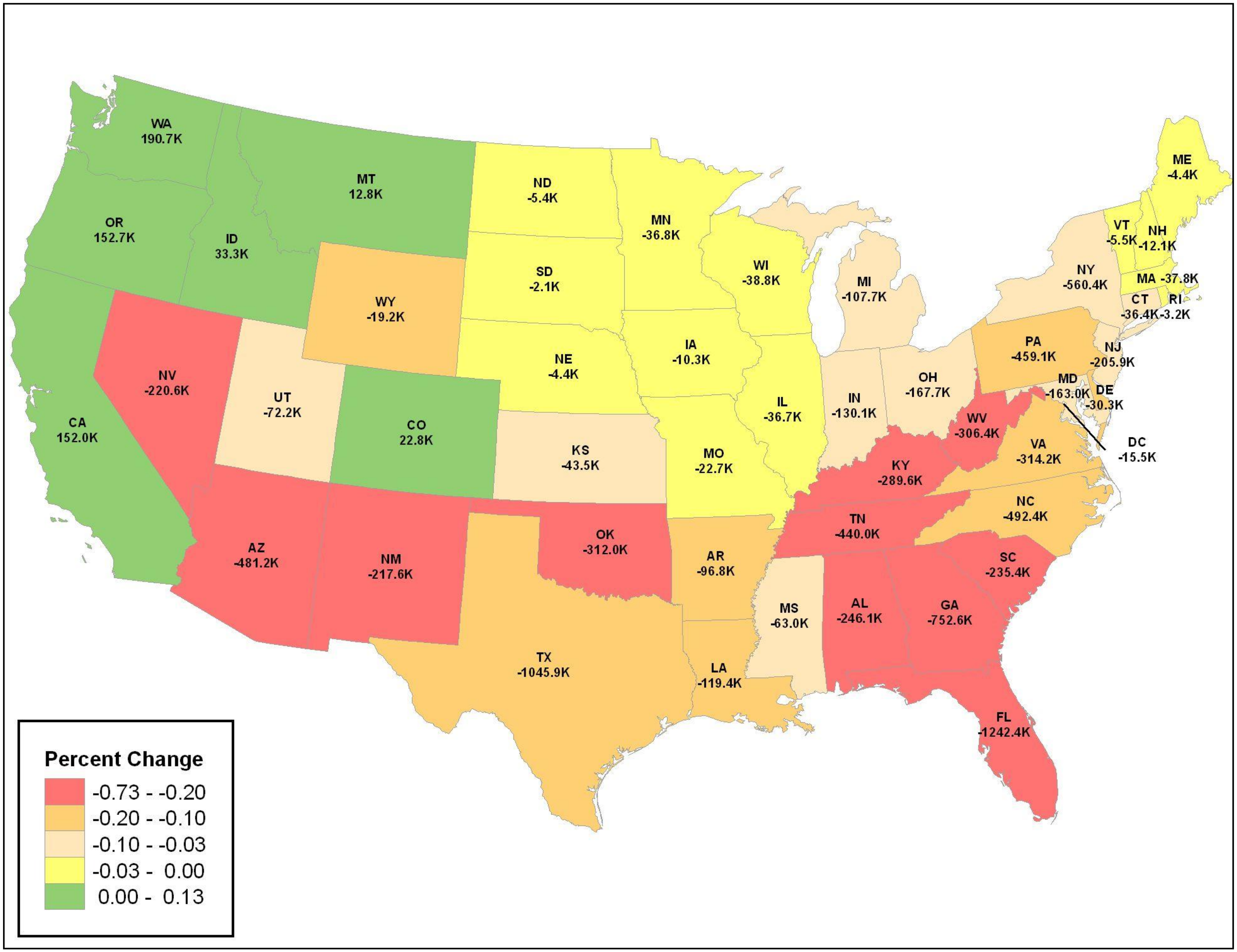

Figure 4-19. Employment risk (employment-years, 0% discount).

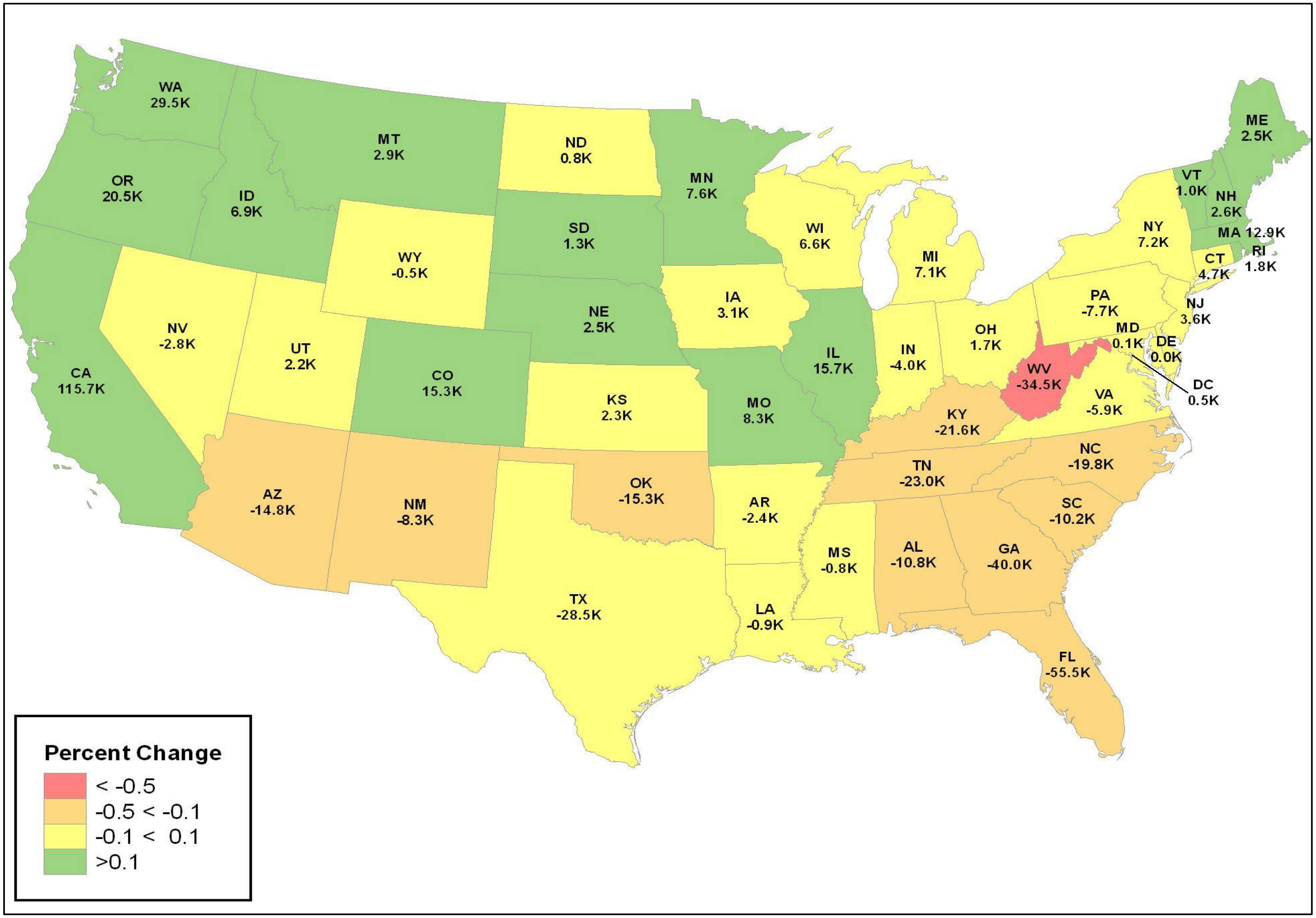

Figure 4-20. Population 2050 risk.

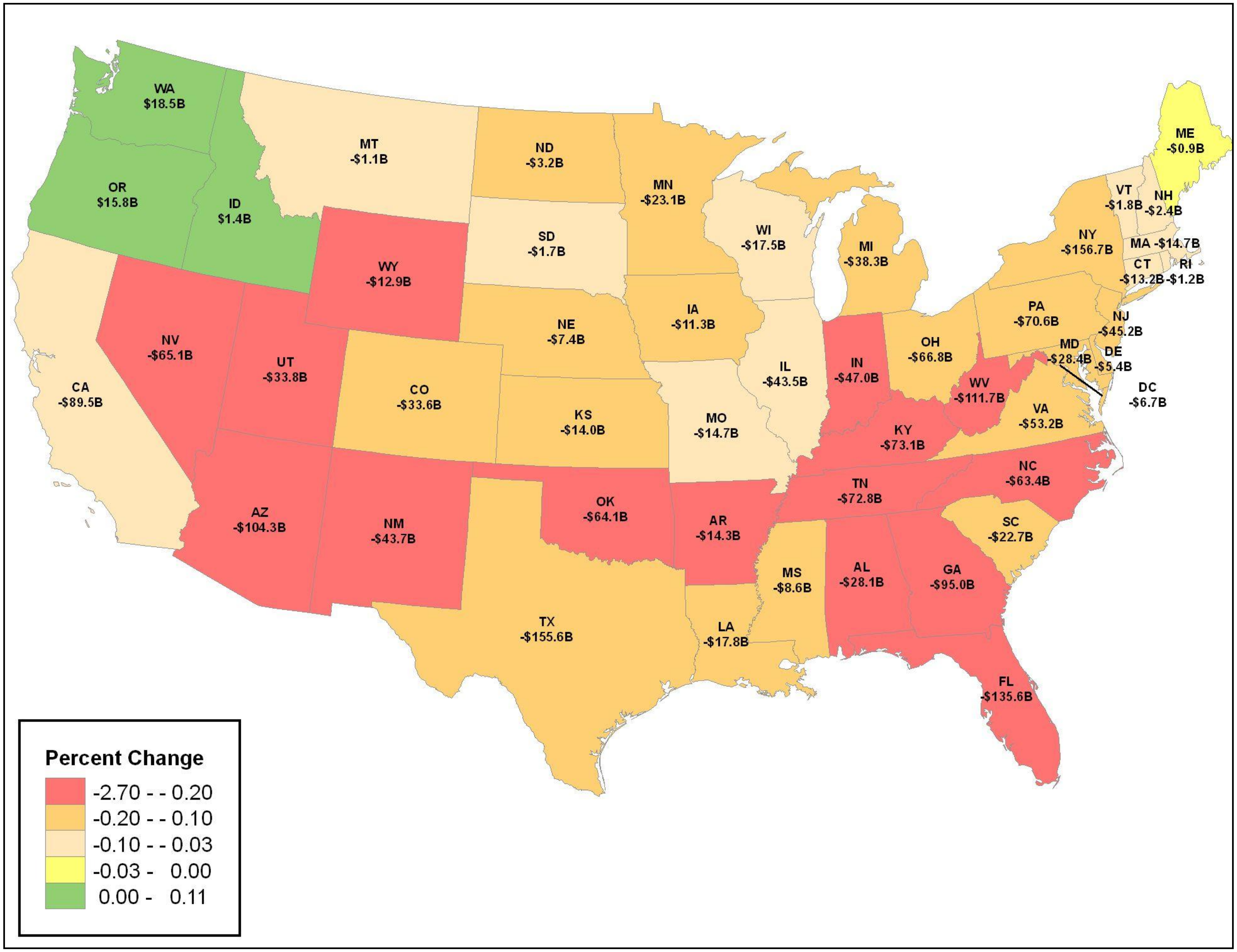

Figure 4-21. Net change in state contribution to GDP 2010–2050, 1% simulation.

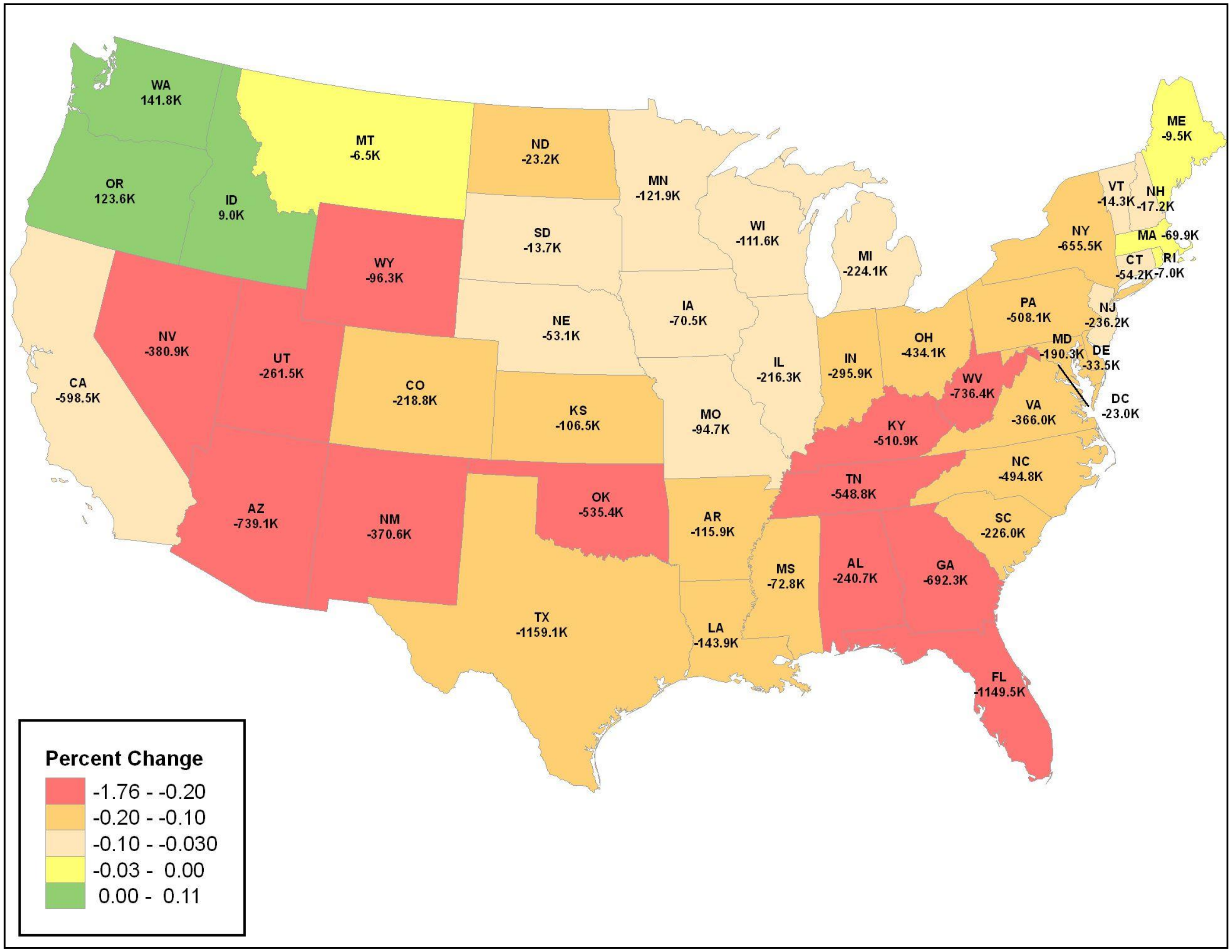

Figure 4-22. Net change in employment-years, 2010–2050, 1% simulation.

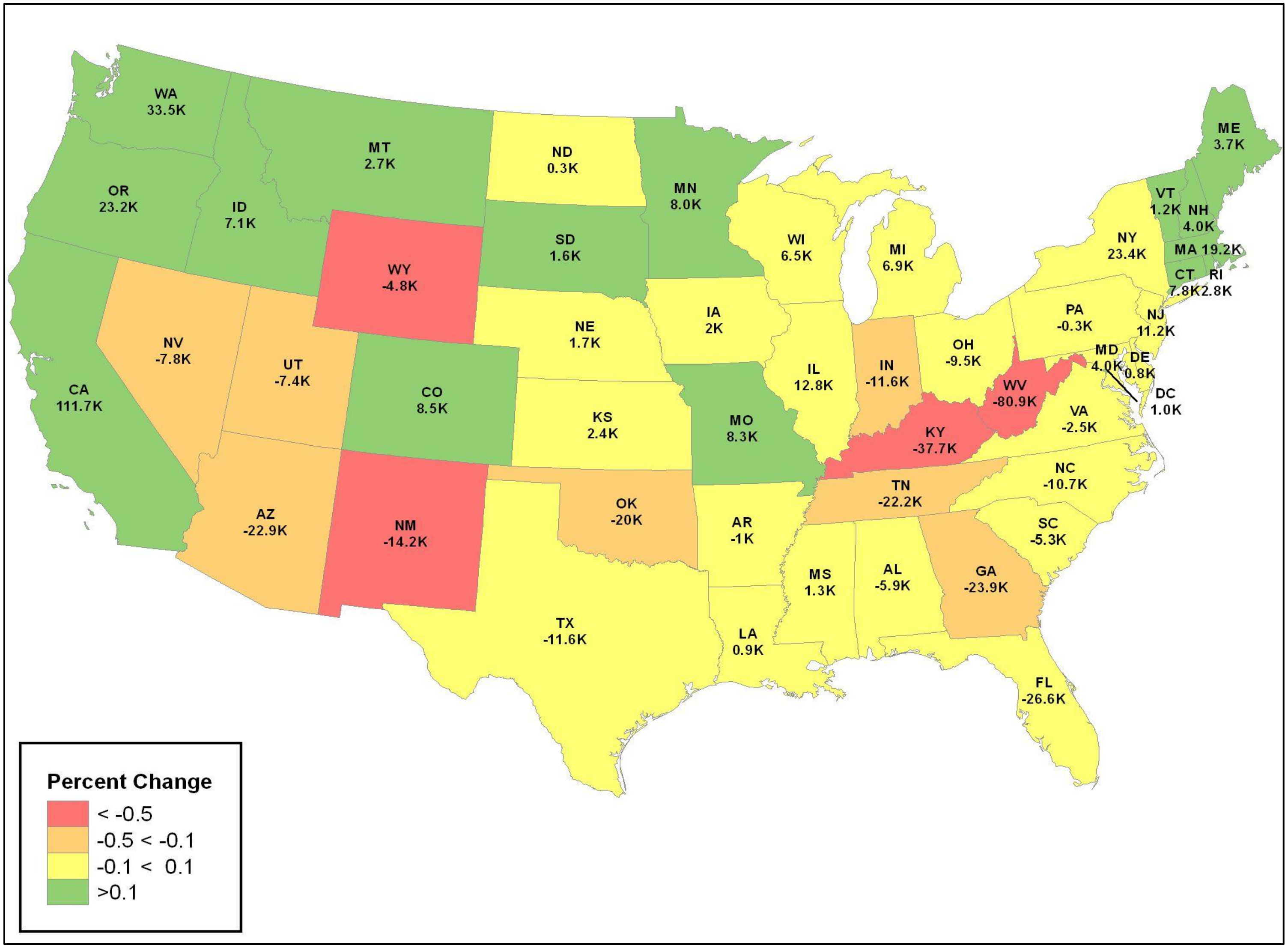

Figure 4-23. Change in 2050 population, 1% simulation.

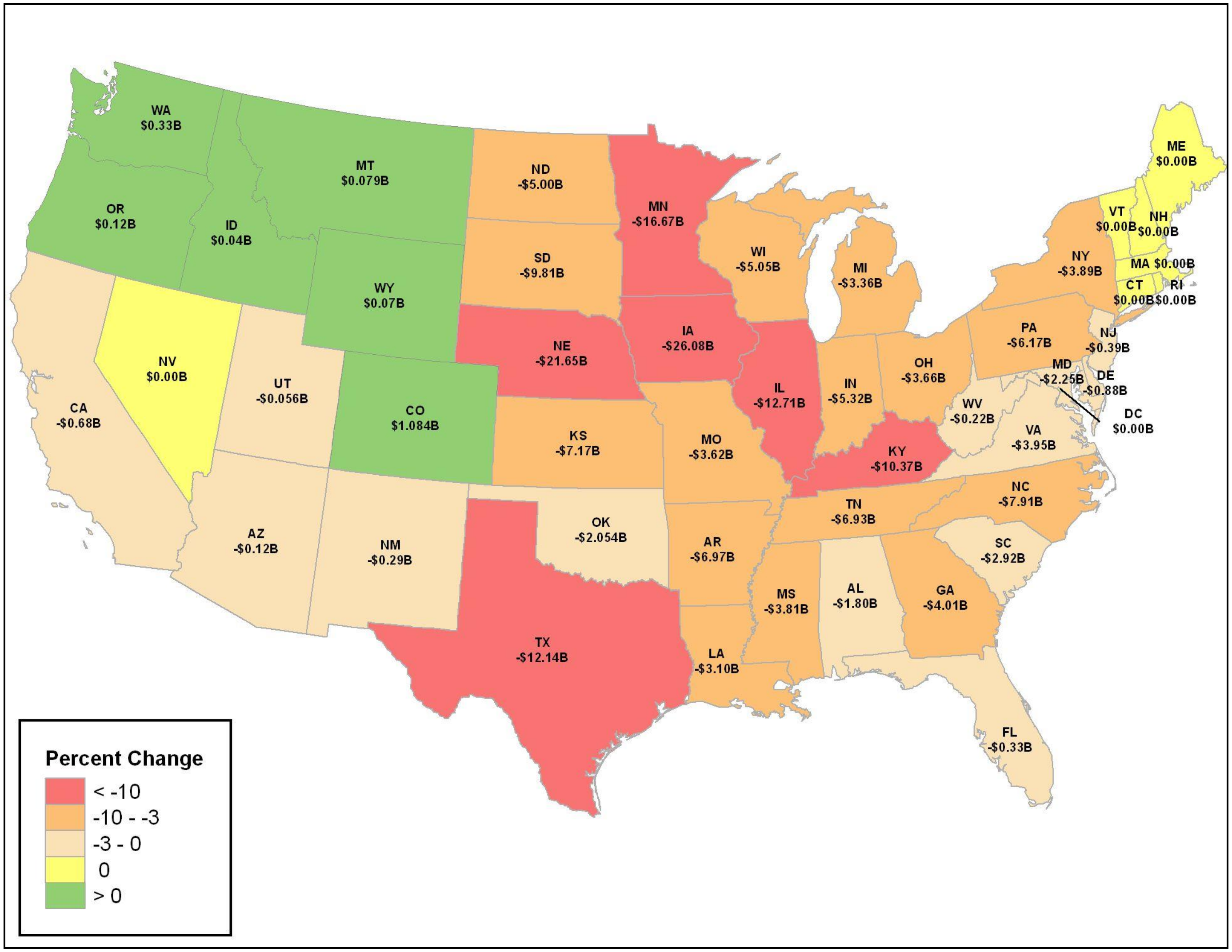

Figure 4-24. Net change in value of corn and soy production, 2010–2050 (states with no recorded production are in white), 1% simulation.

Table 4-9. State-Level Impacts at the 1% Exceedance Probability

1% Case

Region	Change in GDP (0% D.R., $B)	Change in Empl. (1K Labor Yrs)	Change in Pop. (1K People)
United States	-$2,058.5	-12,960.7	0.0
Alabama	-$28.1	-240.7	-5.9
Arizona	-$104.3	-739.1	-22.9
Arkansas	-$14.3	-115.9	-1.0
California	-$89.5	-598.5	111.7
Colorado	-$33.6	-218.8	8.5
Connecticut	-$13.2	-54.2	7.8
Delaware	-$5.4	-33.5	0.8
District of Columbia	-$6.7	-23.0	1.0
Florida	-$135.6	-1,149.5	-26.6
Georgia	-$95.0	-692.3	-23.9
Idaho	$1.4	9.0	7.1
Illinois	-$43.5	-216.3	12.8
Indiana	-$47.0	-295.9	-11.6
Iowa	-$11.3	-70.5	2.0
Kansas	-$14.0	-106.5	2.4
Kentucky	-$73.1	-510.9	-37.7
Louisiana	-$17.8	-143.9	0.9
Maine	-$0.9	-9.5	3.7
Maryland	-$28.4	-190.3	4.0
Massachusetts	-$14.7	-69.9	19.2
Michigan	-$38.3	-224.1	6.9
Minnesota	-$23.1	-121.9	8.0
Mississippi	-$8.6	-72.8	1.3
Missouri	-$14.7	-94.7	8.3
Montana	-$1.1	-6.5	2.7
Nebraska	-$7.4	-53.1	1.7
Nevada	-$65.1	-380.9	-7.8
New Hampshire	-$2.4	-17.2	4.0
New Jersey	-$45.2	-236.2	11.2
New Mexico	-$43.7	-370.6	-14.2
New York	-$156.7	-655.5	23.4
North Carolina	-$63.4	-494.8	-10.7
North Dakota	-$3.2	-23.2	0.3
Ohio	-$66.8	-434.1	-9.5
Oklahoma	-$64.1	-535.4	-20.0
Oregon	$15.8	123.6	23.2
Pennsylvania	-$70.6	-508.1	-0.3
Rhode Island	-$1.2	-7.0	2.8
South Carolina	-$22.7	-226.0	-5.3
South Dakota	-$1.7	-13.7	1.6
Tennessee	-$72.8	-548.8	-22.2
Texas	-$155.6	-1,159.1	-11.6
Utah	-$33.8	-261.5	-7.4
Vermont	-$1.8	-14.3	1.2
Virginia	-$53.2	-366.0	-2.5
Washington	$18.5	141.8	33.5
West Virginia	-$111.7	-736.4	-80.9
Wisconsin	-$17.5	-111.6	6.5
Wyoming	-$12.9	-96.3	-4.8

Obs.: Changes in GDP and employment are summed over the 2010-2050 period; population is the 2050 value.

4.5 Placing the Results in Context

This section contains the national, sectorial, and state-level results of our analysis. It provides an uncertainty-aware estimate of the risk from climate change through 2050 in the absence of policy. These estimates offer a foundation for comparing the benefits of acting to mitigate climate change to the cost of inaction.

The interaction of states and industries means that an impact analysis that considers a state or industry in isolation will miss impacts that could reverse the results. Further, low-probability, high-consequence conditions may dominate the total risk of climate change for states and industries. Some states and industries are affected much more than others. Because of evolving interactions among the responses of states and industries, the impacts of climate change for a particular state or industry can vary in direction (positive or negative) and extent (large or small) from year to year. Similarly, the climatic conditions associated with different exceedance probabilities can produce swings in the direction and extent of impacts over time. States with negative impacts in the "best estimate" (50% exceedance probability) simulation can show benefits in the extreme (1% exceedance probability) simulation. Certainly, the reverse is also true. With diminishing (more extreme) exceedance probabilities, the impact of climate change, in general, sweeps from the Southwest to the Northeast. The relative extent of impacts by state and by the geographical concentration of selected industries shifts with the exceedance probability as climate change moves more intensely across the nation.

The aggregate economic cost in a given state may mask underlying tension. Some sectors, such as agriculture, may experience strong negative impacts while other industries, such as construction, may experience growth. The net reported impact for the state may be strongly positive. In economic assessments, the adaptation to the negative effects of climate change produces new economic activity (i.e., investments) reportable as a benefit. The added costs of the adaptation will generally, however, result in reduced relative competitiveness with associated long-term reductions in economic activity and employment.

The reported summary risk (or total risk) for each state and industry represents the value of mitigating those impacts. The summary risk quantifies the net impact cost of climate change over the full range of possibilities (uncertainty) and consequences. That is why the summary risk also reflects the total risk. It is the value of insuring against those impacts, and it is the economic justification for policy to mitigate them. Risk comes from uncertainty, not certainty. The greater the uncertainty, the greater the risk. *It is the uncertainty associated with climate change that validates the need to act protectively and proactively.*

In the near term, the summary risk at the aggregate national level is less dominated by low-probability events. With the current understanding of climate change through the year 2050, the diversity of resources and climatic conditions across the nation allows adjustments in response to climate change in one region of the nation to partially compensate for those in another region. For the impacts estimated through 2050, the nation as a whole has the resilience to accommodate the impacts "on average." Thus the "best estimate" (average) impacts at the national-level only modestly underestimate the total risk of climate change through 2050.

The results of this study only extend to the year 2050. Impacts beyond 2050 are expected to be exponentially greater, and the results here cannot be generalized to the more severe consequences and more complex impact relationships that may occur in a more distant future. We emphasize summary risk, but some sections of the report do provide added information for 50%, 10%, and 1% exceedance probability conditions. Appendix E shows a very detailed view of impacts at conditions associated with a 1% exceedance probability.

For the present, the impacts and risk noted in this section of the report should help governments and businesses weigh their options for responding to the risk of climate change in the near term. This report provides the cost of inaction. Decision makers can now compare it to the net benefits of any mitigating actions they may pursue.

5 Summary

In this section, we review the primary outcomes, considerations, and limitations of this work. Our purpose is to develop a risk-assessment methodology for dealing with the uncertainty of climate change. To demonstrate this approach, we use the uncertainty in modeled future levels of precipitation associated with climate change as an input to a hydrological analysis that we then use as input to forecast derived macroeconomic impacts. We derive a proxy measure of climate uncertainty from an IPCC climate-model simulation ensemble to drive predictions of the economic cost from climate change for various exceedance probabilities of precipitation. Integration of the cost over the full range of uncertainty represented by this ensemble then characterizes our estimates of the risk from climate change to the GDP through the year 2050.

Our risk assessment only considers the loss in the absence of mitigation or any other climate policy. The value of the loss, on the order of a trillion (2008) dollars for the United States, thus, can be interpreted as an upper limit on how much society could be willing to pay for a successful mitigation of climate change, even over the near term. Consideration of longer-term (post-2050) impacts from climate change would imply a larger cost because of the accelerating climate change, but these more temporally distant impacts are difficult for constituencies to grasp.

The U.S. state-level and industry-level impacts are far from uniform. Some states experience significant swings and large disparities compared to other states. The same lack of uniform impacts is true for industry. Population and employment changes produce similar disparities among the states. Population migration has a significant effect on final outcomes. States that initially experience positive impacts may experience negative impacts in later years, and vice versa.

Conducting an integrated analysis of detailed climatic, hydrological, and economic impacts at the resolution of counties, states, and industries across the range of exceedance probabilities required for a meaningful risk assessment is a relatively complex process. The hydrological and macroeconomic consequences from varying levels of climate change can often defy preconceived notions. This study, however, indicates that the losses associated with the 50% exceedance probability only modestly underestimate the value of the total risk over the full range of exceedance probabilities. This relationship of the 50% exceedance-probability to the total risk is most probably not robust. As advances in climate modeling modify the understanding of best-estimate impacts and the uncertainty characteristics of the climate models, the total risk could be much larger than that associated with the 50% exceedance probability. In the present, this outcome means that current “climate impacts” studies focusing on only the “best estimate” of impacts through 2050 produce national results that can support the policy debate and do corroborate the work here. Nonetheless, states and industries can have impacts dominated by the low-probability, high-consequence tail and by interactions with other states and industries. Consequently, existing “best estimate” studies of individual states and industries can provide useful insights, but an integrated risk assessment appears to be required for a meaningful evaluation of state- and industrial-level risk.

We feel the risk-informed approach used in this work relates physical climate science to the societal consequences and thus directly helps inform policy debate. The integrated process of (1) explicitly recognizing uncertainty in climate-change forecasts, (2) transforming climate-change phenomena into physical impacts that affect economic and societal processes, and (3) converting those physical impacts to time-dependent changes in economic and societal conditions provides the end-to-end assessment capability recommended by the Obama Administration (Holdren 2009). By knowing what aspects of climate change have the most severe human consequences, this type of analysis can also guide and prioritize the scientific research to better quantify the most critical phenomena.

No amount of research can ever eliminate the uncertainty in assessing future conditions and the risks those conditions impose. Because the future may occur before all stakeholders judge that the uncertainty has been adequately reduced, decisions must be made, as they always have been, in the presence of uncertainty. Risk is a function of uncertainty, and the more uncertainty, the more risk. Thus, analyses such as these are required for informing decision making. They support the justification for making decisions because of uncertainty rather than despite uncertainty.

Our detailed, time-dependent approach to the analysis shows the additional early consequences of the volatility in climate change. The impacts across 70 industries and 48 states demonstrate the interrelationships that produce consequences different from those consequences that would be indicated by the analysis of individual states or economic sectors in isolation. To date, this is the first study to address the interactive effects of climate change across the U.S. states and to deal explicitly with the problems of interstate population migration as a consequence of climate change.

Our economic analysis follows the year-by-year impacts associated with year-by-year variability in climatic conditions rather than the more conventional approach of considering gradual change through the years of the analyses. The results of our simulations suggest that the economic consequences of variable global climate change may cause more substantial year-to-year disruptions than climate change would cause if it followed a smooth monotonic trend. A state then lives with those adaptations (and costs) into the future even if climate conditions (temporarily) improve. The added costs often lead to enduring lower levels of industrial output and real disposable personal income beyond what would occur if climate change were a smoothly unfolding process.

We note four primary limiting assumptions in our work. We do not believe they significantly alter our results:

1. A more expansive effort would systematically vary the climate models to establish the key uncertainties relevant to the economic impact analyses. We could include uncertainties associated with the hydrological and macroeconomic models, although that approach would complicate the understanding of how the climate component of the uncertainty affects future risks. Further, a definitive uncertainty analysis of climate models is currently beyond the near-term capability of supercomputing resources and climate science.

2. In this study, we have judgmentally selected water consumption, as opposed to water usage, as the limiting basis for water availability. We also have assumed that legal constraints would dominate supply constraints for the downstream availability of water. Further, we employ a constant proportional relationship between precipitation and water supply. As such, we also have argued that the variation in evapotranspiration due to climate change produces inconsequential second-order effects. A more thorough study could better explore these possible limitations. We believe that the incorporation of such improvements would show the current analysis underestimates the impacts and risks.

3. The technical costs of reducing the water demands of industry and consumers to match the water supply underpin a large part of the macroeconomic analysis. We have based these costs and determined the options available to industry by applying a limited number of studies—studies that were developed for purposes unrelated to the reduced precipitation from climate change. Further, we have used the same unit costs for each state. While we would not expect improved costs to dramatically change the interstate relationships contained in the analysis results, improved costs could alter the total estimated risk from reduced precipitation. Because we have not considered the locational constraints on reducing water usage, such as limitations on the physical space to place equipment, we would expect a more thorough evaluation of technology options to show increased costs.

4. The modeling of the climate risk associated with reduced precipitation must recognize the existence of water rights. Existing water rights, which are based on extensive historical precedence, are fraught with complex legal, political, and social implications. The legal specifics of water rights vary widely from state to state and are unlikely to change dramatically over the analysis time frame. In addition, the allocation of water under enduring climatic water shortages remains largely undefined. Agriculture often has grandfathered rights to water resources, yet under the currently increasing routine instances of limited water availability, compromises, purchases, and the transfer of rights commonly occur. The modeling assumes, to the extent possible, the enforcement of interstate water rights. Thus a shortage in one state, because of defined water allocations, does not necessarily result in a shortage in the downstream state. In this study, we use a simple heuristic when climate change causes reduced water availability. The heuristic assumes that high-value (monetarily and politically) users can purchase rights, but only to the extent where the proportional shortage to other users, such as agriculture or mining, is twice that of the high-value users. The difference in the allocation is associated with payments from the high-value activities to the low-value activities to pay for the water transfer.

Despite the limitations of the current work, we feel it does establish a process for improved and more-meaningful risk assessments of climate change than is currently present in the literature. For the future, we believe that what is more important than refining state-level hydrological conditions and adaptation costs is determining the risks from climate change on international strategic supply chains and the stability of linchpin nation-states. The consequences of climate change for these issues may affect U.S.

interests more than the internal U.S. response to climate-change phenomena. We are pursuing these concerns in our follow-on work rather than directly extending this study.

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Appendix A. Hydrological Modeling

The hydrological model used in the study was adapted from modules embedded in the broader decision-support framework for integrated energy-water planning and management depicted in Figure A-1 (Tidwell et al. 2009). The formal name of this Sandia product is the Energy Water Model. The model was originally developed to study future water usage in the Rio Grande Valley of New Mexico. It has subsequently been enhanced to more completely address climate-change issues, and its geographical data set has been expanded to accommodate the entire United States. In this study, we use elements of the model that pertain to the simulation of future water demand as well as to the identification of regions of potential future water stress. These simulations are possible at each of four reference scales: national, state, county, and watershed.

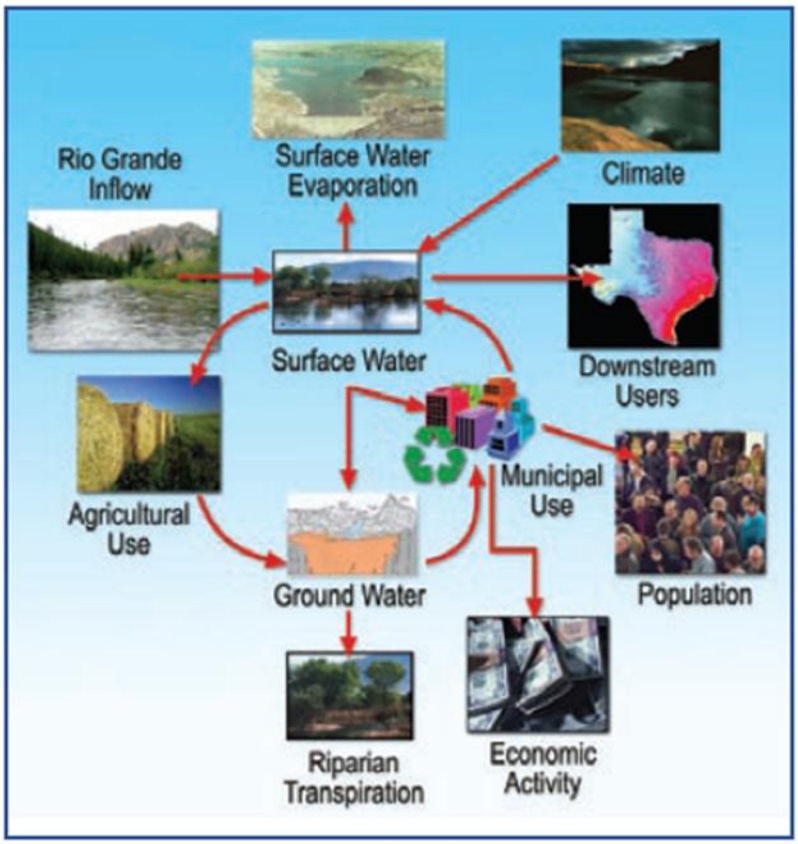

Figure A-1. The Sandia hydrological model (subset of modules used for this study).

We calculate water demand individually for six different use sectors: municipal (including domestic, public supply, and commercial), industrial, electrical power production, agriculture, mining, and livestock. Water use and water consumption are tracked separately for each of these sectors, as are the resulting return flows. Water use denotes the temporary withdrawal for some purpose, such as cooling, and then returning the water to its source, such as a river, for future use by downstream entities.

Consumption denotes a withdrawal of water, such as for crop irrigation and soft drink production, where it becomes unavailable for other purposes. Statistics of water use published by the U.S. Geological Survey (USGS) serve as the primary data source for the analysis. Specifically, data from the 1985, 1990, and 1995 campaigns provide the most comprehensive picture of water use in the United States and hence form the calibration and initialization basis of this analysis (USGS 2009).

We model municipal water use and consumption at the county level and subsequently aggregate these data to the state level. The values for water use in 1995 serve as the initial conditions for the model. The analysis for this study begins in 2000. Future rates for water use and consumption are calculated as the product of the per capita water use and consumption and the population. Projections of population change for individual states are based on output from our macroeconomic referent (the REMI model), whereas the per capita rates for water use and consumption are extrapolated according to regression equations that are fitted to the published USGS rates for water use and consumption. The maximum change in the per capita water use and consumption is capped at ±20% simply to reflect the fact that changes beyond this level generally require the physical structure of the water supply and demand system to change beyond what the existing system can accommodate.

We derive water demand in the industrial, mining, and livestock sectors in a fashion similar to how water demand is handled in the municipal sector; however, we calculate use and consumption rates as the product of the gross state product (GSP) and the associated water intensity (e.g., gallon of water per dollar of the GSP). Projections for the GSP are based on output from the REMI model. Projections of water intensity are based on historical trends and forecasts (USGS 2009).

We model increases in thermoelectric water demand as the product of new power-plant capacity and the water-use rate per kilowatt-hour (kWh). For consistency, we take projections of new growth in power-plant capacity directly from the REMI model. We assume that thermoelectric water-use rates are equal to the 2004 average of the amount of water need to cool a thermoelectric power plant per kWh. For cooling, the model distinguishes the use of ocean water from fresh water.

Water demand in the agricultural sector considers losses from direct use at farms and from conveying water to farms or fields, as well as from the direct consumptive use of the crop itself. Estimated losses are taken directly from published USGS data. We calculate the consumptive losses from crops as the product of historical average irrigation rates for specific crop types and the associated irrigated acreage (USDA 2008). Thus, for each crop considered, we multiply the amount of acre-feet of water used for irrigation of the crop times the average number of acres farmed of the crop.

Key to this analysis is determining at what point a region will begin experiencing water stress. That is, at what point will the available water supply be insufficient to meet all projected water demands? This determination requires some measure of the available water supply. However, detailed current water-supply values for each region of the United States are unavailable, and calculating these values is well beyond the scope of this study. As such, we use a proxy to water supply that is based on the long-term mean (average) gauged flow data, which are available at the USGS four-digit hydrologic unit classification level (Stewart et al. 2006). The long-term averages for the regions are further modified by sequentially subtracting increases in consumptive water use from upstream basins (to account for the effect of growing water use on the availability of water). The model includes projections on the use of ground water and implicitly considers jurisdiction rights on downstream water usage. For this analysis, the ratio of runoff to precipitation is assumed to be adequately constant for determining water availability. Although studies indicate that there will be a change in this ratio, the statistics remain inconclusive about the amount of change (Sheffield and Wood 2008; Seager et al. 2008). Further, any such change in the ratio of runoff to precipitation is inconsequential relative to the impacts considered in this study, as previously noted in Section 2.6 of the main text.

To project potential water stress at the state level, the model calculates the ratio of water supply to projected demand. Three thresholds are used to determine the potential water stress of the individual states based upon the categorization scheme presented in Table A-1. If the ratio of water supply to projected demand is less than 2 (i.e., the water available is less than twice the amount of water needed), the state is assumed to be using essentially as much water as is available in a normal year. Thus, any new water use or drought would immediately result in a water shortage for the states (Taylor 2009) in the "Current < Normal" category, i.e., Arizona, California, Nevada, and New Mexico. If the ratio of water supply to projected demand is between 2 and 10, the state is assumed to experience a water shortage whenever the supply drops below 60% of the long-term average. States subject to this threshold are listed in the category named "Current < 60% of Normal." Finally, all other states are assumed to experience shortages only when the water supply drops below 40% of average and are listed in the category named "Current < 40% of Normal."

Table A-1. Water-Shortage Thresholds by State

Current < Normal	Current < 60% of Normal	Current < 40% of Normal
AZ	CO	AL
CA	CT	AK
NV	DE	AR
NM	FL	DC
	GA	HI
	KS	ID
	MA	IN
	NE	IA
	NJ	KY
	NC	LA
	OK	ME
	RI	MD
	SC	MI
	TX	MN

Current < Normal	Current < 60% of Normal	Current < 40% of Normal
	UT	MS
	VA	MO
	WY	MT
		NH
		NY
		ND
		OH
		OR
		PA
		SD
		TN
		VT
		WA
		WV
		WI

The three categories in Table A-1 relate to the states' current capabilities for storing water. The states in the "Current < Normal" category generally have considerable water-storage capacity, typically in the form of dam systems that can accommodate significant fluctuations in precipitation. States in the "Current < 60% of Normal" category typically have less storage capacity in place. Those states in the "Current < 40% of Normal" category seldom have storage capacity capable of accommodating drought conditions. For each year, climate data are passed to the hydrological model for it to determine where water stress will occur. Where precipitation ratios (current/normal) fall below the above thresholds, apparent water shortages are indicated. Shortages are not evenly distributed across the sectors, but rather are weighted more heavily toward agriculture, mining, and livestock. Specifically, two-thirds of the proportional water-shortage burden lies in agriculture, mining, and livestock, where each is administered according to its relative share of the demand. These shortages are calculated as a ratio of desired water use compared to available supply for the sector. This availability is passed to the REMI model for evaluation of the economic impacts.

The impacts of water availability on crop yield are calculated within the hydrological model. These yield calculations are based on a model developed by McCarl et al. (2008). The hydrological model is empirically based on the historical impact of climate changes of the crop yield distribution, considering temperature, precipitation, variance of intra-annual temperature, a constructed index of rainfall intensity, and the Palmer Drought Severity Index (PDSI). For our analyses, these data are available or derivable from the climate-model results within the PCMDI data set discussed in the main text. We assume that rainfed crops depend solely on precipitation, while irrigated crops depend on both irrigation and rainfall. Specified precipitation and temperature conditions come directly from the climate model, while the percentage of irrigation is based on the severity of water shortage in the individual states.

Visit https://waterportal.sandia.gov/modelingteam/energywater/Models for further information on the Energy Water Model.

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Appendix B. Economic Impact Methodology

The material in this appendix is derived from Warren et al. (2009). The economic impact methodology was designed to answer two economic questions:

1. What does a physical climate change mean economically?
2. How can this change be incorporated in a macroeconomic model?

To answer the first question, we use the forecasts of hydrological changes reported by the Sandia hydrological model noted previously. Table B-1 lists the types of hydrological changes forecast by this model; each of these annual variables is forecast by U.S. state over the 2010 to 2050 period.

Table B-1. Variables Used to Report Hydrological Impact Forecasts

Variable	Description
$\alpha_{x,t}^{i}$	Relative production (compared with a base year) for crop *x* (both irrigated and nonirrigated crop production, combined)
H_t^i	Fraction of normal water availability for municipal consumption
E_t^i	Fraction of normal water availability for thermoelectric generation consumption
HP_t^i	Fraction of normal hydroelectric power production
I_t^i	Fraction of normal water availability for industrial consumption
M_t^i	Fraction of normal water availability for mining consumption

As described in the sections below, we translate these hydrological impacts to direct economic impacts by developing a set of assumptions about the direct economic impacts of each, model these impacts, and then use publicly available data to quantify the actual direct economic effects. We then enter these direct effects into the REMI model to estimate the total (direct plus indirect) economic impacts over the 2010 to 2050 period.

B.1 Climate-to-Economy Modeling Assumptions to Address Uncertainties

This study does not exogenously adjust the technological assumptions inherent in the base-case forecast of the REMI model. Additionally, the study maintains the REMI price-elasticity relationships that simulate consumer responses to rising prices. In general, this response implies substitution of less-efficient production technologies for the use of more-efficient production technologies within the economy. For example, the elasticity relationships do implicitly capture the substitution of incandescent lighting for fluorescent lighting and the purchase of high-efficiency appliances, but these consumer behaviors are economically motivated. We do not adjust the elasticity relationships to include any additional altruistic behaviors to avoid climate change.

To translate each hydrological change into a direct economic impact, we make a set of economic assumptions, models, and calculations based on the type of change and the sectors in which these hydrological changes occur. Each sector is described below, in turn, beginning with two assumptions that apply across all the nonfarming sectors. These assumptions simplify the economic methodology and reduce the uncertainties.

1. For inland facilities, we assume that investments can be made quickly as conditions warrant, such as imposing close-cycle cooling systems or even dry cooling. We further assume that these modifications could happen without the significant shutdown of capacity. States that are adjacent to oceans will have access to desalinated water.

2. Retrofits to conserve water are made instantly. In reality, there may be some delays in producing machinery for the retrofits, which could lead to short-term shutdowns of facilities in the various sectors. We assume that these shutdowns will likely be relatively minor and that postretrofit production can largely compensate for production reduction during the shutdown. Thus, we ignore the cost impacts form the shutdown itself.

B.2 Modeling Agricultural Impacts

To model the effects of changes in agricultural productivity on the U.S. economy, we develop separate strategies to estimate the impacts to (1) farm industries and their suppliers and (2) nonfarm industries that use farm outputs as inputs to their own production.

B.2.1 Impacts to Farming Industry

As with all of the climate-to-economy modeling, the estimates of direct economic impact need to be quantified information (i.e., variables) that can be input directly into the REMI model. The REMI model does not endogenously (i.e., internally) simulate farming activity,[15] but it does include a translator module that allows users to model impacts to sectors that are not explicitly captured in the model, such as the farming sector. For each state and year in the simulation period, the translator module takes as an input the change in the total value of production for that industry and “translates” it into impacts to a broader set of industries. For farm industries, the translator module

[15] This assumption is inherent in the REMI model. It may be justified economically because a principal factor in agricultural production is land, which—unlike capital or labor—is immobile. Furthermore, agricultural markets are international in scope. Thus much of the supply and demand and agricultural markets is largely exogenous (i.e., external) to the United States.

calculates estimates of the changes in government spending, farm employment, farm compensation, and intermediate demand to 65 other industries within the particular state. These translated variables are then used as the inputs to the REMI model. The reduction in output is based on the change in agricultural productivity coming from the hydrological model discussed in the previous appendix.

B.2.1.1 Modeling Assumptions

Given that the farming industry is complex and that behaviors of individual farmers depend on a wide range of factors that are hard to capture with the REMI translator module, we make a number of simplifying assumptions:

- The climate-based changes in hydrology only impact agricultural production in the REMI model for the combined irrigated and nonirrigated crops as forecast separately by the Sandia hydrological model. We do not, for example, incorporate price-based decisions made by farmers to produce or not produce crops. The hydrological model implicitly contains the many physical factors and human factors (e.g., differences in fertilizer applications due to fertilizer prices, different water availability for irrigated versus nonirrigated land), and these models incorporate some factors like soil productivity and, to some extent, farmers' decisions about when to apply fertilizer and how much fertilizer to apply based upon changes in rainfall.

- The changes in corn and soybean production are considered representative of cereal corps. Corn and soybean farming have the greatest shares of production. According to the National Agricultural Statistics Service, in 2008 the production of corn for grain was $47.4 billion, and the production of soybeans was $27.4 billion. By comparison, the production of all "field and miscellaneous crops" was $134 billion, the production of "34 major vegetables" was $10.4 billion, and fruit production was $16.5 billion (USDA 2009a). The third largest crop is hay ($18.8 billion), whose productivity is not modeled within the Sandia hydrological model. Changes to crops other than cereal crops are neglected, but the combined change in the corn and soybean productivity is used as a proxy for productivity in all farming inputs.

- Absolute and relative crop prices are held at constant world prices over the time frame of the analysis. Agricultural commodity prices actually fluctuate on a day-to-day basis based on events in world commodity markets. By affecting agricultural productivity, global climate change will affect global commodity prices. It is uncertain how the international markets for agricultural commodities will respond to global climate change.[16] Because our analysis is strictly U.S. centric, we assume that relative global prices do not change. Local U.S. agricultural prices can change as costs change.

[16] A global model of how agriculture changes its productivity in response to climate change may provide a better idea of whether agricultural commodities will become more or less expensive. Even with such a model, many factors remain that will lead to substantial uncertainty about the overall effect of climate change on commodity prices.

- The only agricultural and water-use substitutions applied in the economic analysis are those substitutions predicted within the hydrological model. No additional substitutions are made on the economics portion of the modeling. In reality, there is a wide range of substitutions that are made by individual farmers, for example: farmers often rotate crops, farmers may change the mix of crops in response to price changes or expectations in productivity, farmers may install irrigation systems or choose not to use existing irrigation systems, and farmers may alter the timing of plantings and fertilizer applications. These considerations are implicitly recognized within the Sandia hydrological model based on historical responses. For this analysis, however, the land in cultivation does not change with climatic conditions. The estimates of the production loss in agriculture due to climate change come from within the Sandia hydrological model. The REMI analysis considers the reduction in production to be the dominant impact. Any additional changes that are outside the scope of this effort are assumed to be secondary.

- We use the exogenous growth pattern for advances in agricultural production technologies that is used in the base case of the REMI model (our macroeconomic referent). In addition to improvements in general framing practices, these changes consider improvements in how intermediate goods and services are used in the production of crops. These improvements over time are applied by the translator module when it converts the agricultural results of the hydrological simulations into input changes to the REMI model. The ratio of the corn and soybean contribution to the GDP to the production of these crops is therefore assumed in the climate-change simulations to grow at the same rate as the REMI model's base-case forecast. For example, if a farmer in the base case produces a bushel of corn in 2050 with half the amount of labor used in 2010 (based on REMI's base-case forecasted improvements), a farmer in the simulations will produce a bushel of corn in 2050 with half the amount of labor used in 2010 even if fewer bushels are produced in the simulations than in the base case. Effectively, our assumption implicitly considers the ratio of the farm GDP to farm production to remain unchanged from what it is in the REMI base case for all our simulations.

- We assume that climate change does not directly affect livestock farming. In reality, livestock farming may be impacted by changes in the price of feed, changes in the productivity of forage eaten by grazing livestock, and water used in livestock farming and manufacturing.[17] Industrial livestock production may be affected indirectly through impacts to the food manufacturing industry. The hydrological model does capture these phenomena, but we consider the impacts secondary to this analysis.

- We do not make adjustments for the effect of climate change on forestry. While it is likely that climate change will affect forest productivity, given the long time constants in silvaculture and the 2050 time horizon of this study, the important impacts on the forestry industry (other than increases in fire destruction, also neglected) occur in time frames beyond this analysis.

[17] Water use in livestock farming is less than 1% of all U.S. water use (Hutson et al. 2004).

B.2.1.2 Modeling Procedures

Because the output of the translator module is proportional to the magnitude of the inputs, we used the translator to develop a standard set of impacts for a $1 million change in the corn or soybean crop production. We can then determine the impact from any change in farm production by simply multiplying the farm loss in millions of dollars by the “standard set.” This linear approximation, which essentially employs a set of multipliers, allows automated calculation of inputs to REMI agricultural-sector based on the output of the hydrological analysis.

We use estimates of corn productivity from the Sandia hydrological model to estimate changes in the REMI model’s grain-farming industry and changes in soybean productivity in the REMI model’s oilseed-farming industry. Changes in production values (measured in dollars aggregated across each state) for each crop, *x*, (that we have entered into the REMI model via the translator module) are calculated as

$$\Delta Y_{x,t}^{i} = Y_{x,t}^{i} - Y_{x,b}^{i} = (\alpha_{x,t}^{i} - 1) Y_{x,b}^{i} \frac{GDP_t^{farm}}{GDP_b^{farm}},$$

where

$\Delta Y_{x,t}^{i}$	=	the change in production for crop *x* in state *i* (an average of 2006 to 2008 data [USDA 2009a],[18]
$Y_{x,t}^{i}$	=	the value of production in year *t*,
$Y_{x,b}^{i}$	=	the average production in the baseline period (an average of 2006 to 2008 data [USDA 2009a]),
$\alpha_{x,t}^{i}$	=	the relative production of crop *x* in year *t* in state *i* to the baseline production (an output of the hydrological model),
GDP_t^{farm}	=	the REMI model’s (exogenous) forecast of national farm GDP in year *t*, and
GDP_b^{farm}	=	the REMI model’s (exogenous) forecast of national farm GDP in the baseline period (an average of 2006 to 2008).

To quantify the input variables that can be used to simulate the impacts, we convert $\Delta Y_{x,t}^{i}$ to millions of dollars and multiply that value by the variables produced by the REMI translator module for each state, economic sector, and year in the forecast period.

[18] Taken as the average of 2006 through 2008 data (USDA 2009a) .

B.2.2 Impacts to Industries That Use Farm Output

In addition to directly impacting agriculture, changes in agricultural productivity will impact the downstream users of agricultural farm output. These users are modeled directly within the REMI model except for the intermediate inputs they purchase from the exogenous farm industry.

B.2.2.1 Modeling Assumptions

Modeling the effects on the downstream users of farm products in this study requires a number of assumptions in addition to those listed above:

- The actual amount that the users of a commodity pay to obtain the commodity includes the cost of transportation. Although this "economic geography" process is modeled in most industries within the REMI model, once again it does not apply to the exogenous farm industry. In this case, the net price of these food commodities is assumed to include transportation costs. If production in a state decreases, net prices are assumed to increase due to the higher costs necessary to transport the commodities.

- We assume that the degree to which an industry is affected by net price changes of farm production is proportional to the total requirements of the particular industry that originates from the farm industry. Table B-2 lists the Bureau of Economic Analysis (BEA) industries that have total requirements of $0.05 or more for each dollar of production, an amount that was chosen as the cutoff for industries modeled in this study. Changes in the net price will change the production costs for the industries shown in the right column of the table. The data in the table were extracted from U.S. Department of Commerce (2008b).

Table B-2. Industries with Total Requirements from Farms of at Least $0.05 per $1 of Output

IO Code	BEA Industry Name	Requirement for \$1 Output (R_x)	REMI Industry/Industries
111CA	Farms	\$1.18	N/A
311FT	Food and beverage and tobacco products	\$0.31	#19: Food manufacturing, #20: Beverage and tobacco product mfg.
113FF	Forestry, fishing, and related activities	\$0.10	#2: Agriculture and forestry support activities; Other
722	Food services and drinking places	\$0.07	#62: Food services and drinking places

- We assume that changes in corn and soy production, when averaged together using a weighted average based upon baseline production of the two crops by state, serve as proxies for changes in productivity for all farm inputs within a state.

- To estimate the direct GDP contribution of crop production, we estimate the ratio of the GDP directly due to crop production to production of corn and soybeans. Between 2006 and 2008, national corn and soybean production averaged $58.1 billion (2000$) and crop production averaged $126 billion (USDA 2009a). During the same time, the average estimated (exogenous) farm GDP in the REMI model was $87.9 billion. In 2006, the measured output in livestock was $112.1 billion) (Figueroa and Woods 2008). Therefore, the estimated ratio is [$126.0 billion/($112.1 billion + $126.0 billion) * $87.9 billion]/$58.1 billion = 0.801.

- The REMI model's projected changes in technology in industries that use farm products as inputs account for the REMI model's forecast changes in food-production technologies. Therefore, only the changes in productivity measured by the hydrological model (i.e., not the REMI model's forecast increases in farm productivity) are used to calculate changes in production costs.

- Final demand from consumers for farm output is small (personal consumption expenditures are $52.9 billion compared with industry output of $294.8 billion). Most consumer demand for farm production comes by way of demand for the production of the industries listed in Table B-2 (e.g., personal consumption expenditures for food and for beverage and tobacco products are $482.5 billion compared with industry output of $722.2 billion and personal consumption from food services and drinking places is $497.8 billion compared with industry output of $614.1 billion (U.S. Department of Commerce 2008b). Therefore, we do not model changes in the net prices of farm production that directly affect consumers although we recognize that the REMI model endogenously (i.e., internally) calculates rising prices to consumers from cost increases in these other industries.

B.2.2.2 Modeling Procedures

Because farm production is a basic input for most of the production in the industries listed in Table B-2, it is difficult to substitute other inputs. An increase in the net costs of farm production will appear to be an exogenous increase in production costs in these industries (because the farm industry is not modeled endogenously in the REMI model). Therefore, we model the increased net costs to these industries by exogenously increasing the production costs in the REMI model. This approach is "used when a specific policy will affect the cost of doing business in a region without directly changing the relative costs of factor inputs" (REMI 2009). Farm input is not included as a factor input in the REMI model.

We assume that if farm production within a state changes, the changes are compensated by imports or exports via rail transportation. Table B-3 gives some average costs of shipping grains by rail, as well as the price of each crop. The "% Rail" column indicates the cost of the rail transportation relative to the price and can be thought of as the increase in net price if a firm had to obtain these grains via rail instead of locally. With these data as a guide, we assume that production costs will increase or decrease by a factor of 20% of the decrease or increase of agricultural production in the state.

Table B-3. Average Cost to Ship Grain by Rail[19]

Grain	Avg. Rail Cost Per Bushel	July 2010 Price Per Bushel	% Rail
Corn	$0.99	$4.75	21%
Soybeans	$1.04	$9.87	11%

We use the following equation to estimate the change in production costs caused by changes in agricultural production in state *i*:[20, 21]

$$\Delta PC\%_{x,t}^{i} = -20\% * R_x * \left(\frac{(\alpha_{corn,t}^{i} - 1) * Y_{corn,b}^{i} + (\alpha_{soy,t}^{i} - 1) * Y_{soy,b}^{i}}{Y_{corn,b}^{i} + Y_{soy,b}^{i}} \right),$$

where

$\Delta PC\%_{x,t}^{i}$ = the percentage change in production costs for industry *x*,

R_x = the total requirements of industry *x* for farm products to produce a dollar of outputs,

$\alpha_{x,t}^{i}$ = the relative production of crop *x* in year *t* in state *i* to the baseline production (an output of the hydrological model), and

$Y_{x,b}^{i}$ = the average production in the baseline period (an average of 2006 to 2008 data [USDA 2009a]).

The term $\Delta PC\%_{x,t}^{i}$ goes into the REMI model as the change in the shares of production costs for the appropriate industry.

[19] The data in the table were compiled from USDA (2009b), the July 2010 futures price (closing price on 5/19/2009 on the Chicago Mercantile Exchange, http://www.cmegroup.com, and calculation of the rail costs as a percentage of the futures price.

[20] In states without either corn or soybean production, this term is assumed to be zero.

[21] Throughout the report, the "*" symbol denotes element-by-element multiplication.

B.3 Modeling Impacts to Municipal Water Use

Municipal water use is one output from the Sandia hydrological model that we do not model directly in the economics model (i.e., REMI) because our internal evaluation indicates that there are many opportunities for substantial municipal water conservation that will be inexpensive and have little effect on the livability of a region. While there is a utilities sector within the REMI model that subsumes the municipal water utilities, municipal water utilities are not modeled explicitly in the 70-sector version used in this analysis. As such, directly calculating the impact of a separate municipal water sector is not possible. Therefore, a number of assumptions need to be made to model the effects of water shortages to municipal water utilities. These assumptions follow.

B.3.1 Modeling Assumptions

- Our review indicates that drought-induced water conservation is relatively easy to conduct. For example, the EPA estimates that 30% of household water is used for outdoor watering (and this is higher in arid regions) (EPA 2008), suggesting that a significant fraction of water consumption would be eliminated in time of drought. Also, the American Water Works Association (2009) estimates that 30% of household water could be saved if all homes installed common water-saving features. Finally, 60% (or more) of household water use could be readily reduced with current, affordable technology.

- Our review indicates that municipal water losses of greater than 60% would have to be made up with more-extreme conservation measures, such as developing new no- or low-water technologies, or increased conservation measures, such as taking shorter showers, washing clothes less frequently, using disposable dishware, eliminating car washes, closing golf courses, or having the population migrate to states with greater water availability.[22]

- Our review indicates that many technologies exist that may help provide long-term sources of municipal water. For example, rain-harvesting technology, water treatment, desalination, and water pipelines could be used to increase supply. We assume that the use of future technology remains the same as today except that desalination may be increased near the coasts. The assumed use of conventional water-conserving technologies is a pragmatic approach to estimating the impacts of reduced water availability.

[22] As for minimum water requirements, the United States Agency for International Development (USAID) recommends 20 to 40 liters per person per day, while a separate study recommends a Basic Water Requirement right of 50 l/p/d (17% of average U.S. household use and 9% of average California household use) (Gleick 1996). The daily per-person minimum requirement of water usage could probably be reduced by more-efficient technologies like composting toilets.

B.4 Modeling Impacts to Power Production

Although agricultural irrigation has the largest consumption of water, thermoelectric power production is the sector with the largest U.S. water usage (Hutson et al. 2004),[23] albeit with only 3% of the national consumption (Feeley et al. 2005). As a result, water shortages could be expected to have significant impacts on electricity supplies. In the total absence of water, facilities could maintain production by dry cooling, thereby eliminating water consumption in thermoelectric generation. New renewable-generation technologies such as wind and photovoltaic facilities would also not need water. In states adjacent to oceans, desalinated water used in evaporative cooling systems and ocean water used in once-through cooling systems provide an even cheaper alternative. To reflect the increased costs of the backstop technology, we model the effect of water shortages on electricity production by increasing the costs of generating electricity in the REMI model.

Additional impacts to power production result from changes in water volumes in rivers and streams that change the available production of hydroelectric power. We model these changes by changing the demand for alternate sources of electricity production in the REMI model.

B.4.1 Thermoelectric Power in States not Adjacent to an Ocean

Because of prohibitive costs, in-land power plants do not attempt to use ocean water and therefore need to reduce their dependence on water availability (e.g., river flow) conditions.

B.4.1.1 Modeling Assumptions

- Thermoelectric power was responsible for 48% of water withdrawals in 2000 (Feeley et al. 2005). However, much of that water (91%) is used in once-through cooling, where most water is returned to the source where it originated, at a higher temperature, and thus is not consumed. The remainder of the water is used in closed-loop cooling systems where most of the water is evaporated, hence consumed. We use this basis to distinguish water consumption from usage, as we incorporate investments to reduce the water needs of the power sector.

- Due to climate change, it is possible that some freshwater sources for once-through cooling will no longer have a sufficient flow of water. Hydroelectric power may be similarly affected by reductions in water flow. We assume the reduced hydroelectric production may necessitate additional supplies of power from alternate sources such as thermoelectric power. We include the impact of developing the alternative production facilities.

- Climate change may also increase the temperature of water and air, which may decrease the cooling efficiency of thermoelectric power plants. Additionally,

[23] Consumption is higher in agriculture because 91% of thermoelectric withdrawals are used in once-through cooling, which consumes very little water.

"warmer water discharged from power plants can alter the species composition in aquatic ecosystems" (Karl et al. 2009). Because the temperature changes in river water are not explicitly considered by the Sandia hydrological model, we do not explicitly consider the economic effects of these changes for the power plants. As noted in Section 2.6, the impact of the changes in efficiency of the power plants is small compared with the cost increases already assumed by retrofitting the cooling system.

- In addition to once-through cooling and closed-loop cooling, there is a third type of cooling referred to as air-cooled (dry) cooling. This expensive but universally applicable technology to combat water shortage is called the backstop technology. This technology consumes little water, and instead works similarly to air cooling by removing heat from steam and transferring it to the ambient air with fans. We assume that electricity producers will retrofit to dry cooling only when that are faced with water shortages, A large portion of thermoelectric power generation involves converting to combined-cycle generation technologies (Powers Engineering 2006), much of which can more easily use dry cooling (and in the event of water shortages, an even greater share will be dry cooling) due to the reduced cooling needs of these plants.

- We use an estimate of the additional cost of dry cooling from calculations made by Powers Engineering (2006) for retrofitting generation in California. The company performed calculations for a hypothetical plant that find the increased cost of generation of converting from once-through cooling to a wet tower will be between $0.0013/kilowatt hour (kWh) and $0.0039/ kWh (against a wholesale price of $0.07/kWh) depending on the capacity utilization of the plant. Powers Engineering also cites projections that dry-cooling retrofits would cost 25% more than wet-tower retrofits, which means that the range would be $0.0016 to $0.0049/kWh. These calculations assume a 7% interest rate and 100% debt financing. A more realistic mix with 55% debt financing, 45% equity financing (taxed at 50%), and property taxes triples the cost in the range of $0.0048 to $0.0147/kWh.

- Retrofits have the additional effect of making power production less efficient. Powers Engineering estimates that cooling will reduce the efficiency of the hypothetical plant and cost an additional 1–2% for retrofitting to wet closed-loop cooling. However, the company does not recommend a value for dry cooling, which is more energy intensive. A power consultant identifies increases of 1.9 % for production costs when retrofitting wet, closed-loop cooling and 4.9% for dry cooling (Maulbetsch 2006). Assuming that wholesale prices of $0.07/kWh can be used as costs, multiplying those prices by 4.9% increases the cost by $0.00343/kWh.

- The increased investments in equipment increases the total cost of retrofits in a range of $0.00823 to $0.01813/kWh. We assume that the high end of the range is correct and that retrofits to dry cooling will increase generation costs by an additional $18.13/megawatt hour (MWh).We assume that the high end of the range is correct and that retrofits to dry cooling will increase generation costs by an additional $18.13/megawatt hour (MWh).

- An alternative backstop technology is gas turbines. The turbines tend to be relatively expensive to use because the price of natural gas is high, and the turbines have low utilization rates because they mainly are used to serve peak demand. For these reasons, we assume that power producers will not switch to gas turbines to mitigate water shortages.

- We assume that once retrofits have been implemented, the electric power in a state will be able to operate fully with the reduced level of water consumption at the increased costs in future years.

As different states have different mixes of once-through cooling, the states are affected differently by water shortages. For example, all cooling in many arid states is done by the wet, closed-loop type because such states lack the water volume required for once-through cooling.[24] However, we assume that water shortages will affect the power production of generation technologies that commonly consume water (i.e., fueled by coal, natural gas, nuclear, other, other biomass, other gases, petroleum, and wood and derived fuels) in proportion to the state's water shortage. This is a conservative estimate for four reasons. First, wet, closed-loop cooling consumes a much greater amount of water than does once-through cooling for the same power production. It is likely that wet, closed-loop cooling would be converted first to dry cooling. This conversion would reduce a large fraction of water consumption but affect relatively little power production. For example, we estimate that in Texas wet, closed-loop cooling consumes 97% of all water consumed for cooling but produces only 62% of power.[25] Our conservative assumption is that a 97% reduction in available water would require that 97% of the power-plant capacity be retrofitted to deal with that water shortage—likely an overestimate. Second, some portion of the power produced in each state, especially the power produced with natural gas, already uses dry cooling. Consequently, fewer power plants within each state would need to retrofit their cooling mechanisms. Third, retrofits would first occur for power plants that operate at a high-capacity utilization rate; thus the costs of a retrofit in reality should be lower for mild water shortages. Fourth, power plants that use ocean water as their source are unlikely to require retrofitting because they consume salt water from a source that is expected to increase in volume.

B.4.1.2 Modeling Procedures

The additional production cost of electric power in each state, *i*, and each year, *t*, is calculated from EIA (2009) as

$$\Delta Y_t^i = \$18.13 * (1 - E_t^i) * X^i,$$

where

[24] Calculated from EIA (no associated date) titled "Annual Steam-Electric Plant Operation and Design Data" using data from 2005.
[25] *Ibid.*

E_t^i = the fraction of normal demand for water by electric power producers that is satisfied and

X^i = the total power production, in MWh, of production in the state in 2007 for power fueled by coal, natural gas, nuclear, other, other biomass, other gases, petroleum, and wood and derived fuels.

Because producers can permanently operate with a reduced supply of water following retrofits, $E_{t+1}^i \le E_t^i$. In years where the electric power available for electricity production decreases (i.e., $E_t^i < E_{t-1}^i$), investment in cooling retrofits is measured by[26]

$$\Delta IN_t^i = \$71.35 * (E_{t-1}^i - E_t^i) * X^i ,$$

which assumes that all investments are made immediately.

The REMI model contains a "Cap and Trade Scenario" testing capability that provides guidance in modeling the economic impacts of cap-and-trade policies. Because cap and trade is likely to impact the electric power generation sector, the REMI Cap and Trade analysis suggests manipulating utility costs. An increase in production costs due to retrofitting equipment to reduce water use, as used in our analysis, is a similar cost increase.

Utility costs are changed by increasing the production costs for the utilities sector. Specifically, we exogenously increase the value of the production costs in the utilities sector by the amount (ΔY_t^i) determined by the above equation. During years where producers must invest in retrofitting technologies, this additional demand (ΔIN_t^i from the above equation) is invested. We then exogenously modify the REMI model's investment spending for what REMI calls "Producer's Durable Equipment." This approach, however, allocates demand generically in a way that overly favors production in industries like computer and electronic product manufacturing. Thus, we use REMI's translator module to adjust these numbers for different types of equipment, such as industrial equipment. Like the translator for agriculture, the equipment translator produces many variables (up to 65) that are slightly different for each region. We estimate that around 60% of additional net demand goes to the machinery manufacturing sector and 33% goes to the electrical equipment and appliance manufacturing sector. To simplify the calculations, we assume that two-thirds of ΔIN_t^i goes to the machinery manufacturing sector and one-third goes to the electrical equipment and appliance manufacturing sector by modifying the REMI policy option for exogenous final demand.

[26] Calculations from Powers Engineering (2006) for a retrofit from once-through to wet-tower cooling are \$100,000/MW of capacity. Using their estimate that dry cooling costs 25% more, this value becomes \$125,000/MW. Using the low-end capacity of 20% (8,760 hours × 0.20 = 1,752 kWh per year), this averages to \$71.35/MWh.

B.4.2 Thermoelectric Power in States Adjacent to an Ocean

If there is a shortage of fresh water, power plants near the ocean can directly use saline water, can have the water shipped inland via a pipeline to the facility, or can convert (municipal) desalinated water for their own use.

B.4.2.1 Modeling Assumptions

In states that are adjacent to oceans, we assume that water shortages experienced by the electric power industry are mitigated by using once-through cooling with saline ocean water or by desalinating water and using it in wet-tower cooling. We assume that thermoelectric generation plants in a state will conserve water by switching wet-tower cooling systems to desalinated water during water shortages.

Because desalination is a proven technology, we assume that any state on a coast has access to desalinated water as a backstop before water shortages become too severe. (In addition, states not on the coast may have access to desalinated brackish water, but we ignore this possibility because it would affect a relatively small population.) In these states, the main consideration for modeling is the increased cost of the desalination process.

Desalinated saline water is more expensive than surface or ground water. A recent study cited the current price of water in San Diego as $0.24/m^3 but the cost of desalination as between $0.64 and $1.04/m^3 (NRC 2008). A review of cost estimates for various technologies conducted by Miller (2003) at Sandia found estimates from 23 studies. For sea water, these estimates ranged from $0.27 to $6.56/m^3; however, the high range is an outlier. Removing one study puts the upper estimate at $1.86/m^3. We assume that the upper estimate is correct and that using desalinated water will increase the cost by $1.62/m^3.

A study of water use by thermoelectric plants found that the mean withdrawals per kWh of electricity for evaporative cooling was between 4.54 and 4.95 cubic decimeters (dm^3) for one kWh, depending on the technology used (Yang and Dziegielewski 2007). Taking the larger value, we assume a value of 4.95m^3/MWh. Thus the additional cost of using desalinated water in wet-tower cooling is $9.21/MWh. Because the cost of using desalinated water is about half the cost of converting to dry cooling ($9.21/MWh versus $18.13/MWh), conservation of water will likely occur by substituting desalinated water.

B.4.2.2 Modeling Procedures

The additional production cost of electric power in each state, *i*, and each year, *t*, is calculated by

$$\Delta Y_t^i = \$9.21 * (1 - E_t^i) * X^i ,$$

where

E_t^i = the fraction of normal demand for water by electric power producers that is satisfied, and

X^i = the total power production, in MWh, of production in the state in 2007 for power fueled by coal, natural gas, nuclear, other, other biomass, other gases, petroleum, and wood and derived fuels (EIA 2009).

In states where cooling retrofits are necessary to conserve water, electricity production could permanently operate with less water. However, in the case of states adjacent to oceans, electricity producers may use desalinated water in one year and return to fresh water in the following years if the shortages are less severe.

As discussed previously, we exogenously increase the value of the REMI "Production Cost" (amount)" variable for the utilities sector by the amount ΔY_t^i determined by the above equation. In addition, we exogenously increase the value of the "Industry Sales/Production" variable for the utilities industry by an amount equal to ΔY_t^i to account for the increased water production that the power generators require from water utilities that provide desalinated water. Increases in production in the REMI model automatically trigger investment in the industry; thus the REMI model automatically accounts for investments that are made to build desalination capacity.

B.4.3 Hydroelectric Power

Hydroelectric plants are fully dependent on water flow. The enduring loss of water requires the construction of new renewable-energy, fossil, or nuclear-powered facilities.

B.4.3.1 Modeling Assumptions

Drought conditions will change rainfall and thus change the volumes of water flowing through rivers and streams. Hydroelectric power creates electricity from the potential energy in water, so lesser or greater flows of water correspondingly reduce or increase the amount of power that can be generated by a hydroelectric plant.

We approximate the marginal cost of producing hydroelectric power as zero because the major costs of producing hydroelectric power are about the same regardless of how much power the plant actually produces. Capital costs to build hydroelectric power generation are sunk costs. Thus the cost of producing electricity is the same no matter how much power is produced. Labor costs are relatively small; the same amount of labor is required from workers, such as guards and operators, irrespective of the level of power production. Hydroelectric power does not use a costly fuel source as does thermoelectric power. Thus changes to hydroelectric power, alone, are not assumed to have any aggregate macroeconomic impact.

Changes to hydroelectric power production will have a macroeconomic impact through substitutions away from or to other forms of production with a greater marginal cost. We assume that reductions in hydroelectric power lead to an equally large increase in demand for thermoelectric power, whereas decreases in hydroelectric power lead to an equally large decrease in demand for thermoelectric power within the state where the hydroelectric power is produced. These changing demands change production levels but not necessarily within the same state—power can be imported or exported outside a region.

We assume a monetary value for changes in demand of \$138.13/MWh, which is equal to the cost of new coal-power generation (\$120/MWh)[27] plus the costs of retrofits to dry cooling towers (\$18.13/MWh—a conservative assumption because cooling "retrofits" will likely be cheaper to implement when designed into new construction).

We do not calculate any changes to demand for other sectors. In reality, an increase in demand for the utilities sector, for example, could reduce demand for other sectors because of price and income effects. However, modeling at this detailed level is beyond the scope of this study. By assuming that there are no changes to demand in other sectors due to changes in demand for the utilities sector, we are setting the bounds of the maximum possible impact.

B.4.3.2 Modeling Procedures

Changes in the demand for alternate sources of power resulting from changes in hydroelectric production are treated in the REMI model as a change in the "Exogenous Final Demand (amount)" variable of the utilities sector. To satisfy changes in demand, the REMI model changes production and investment in capital stock (e.g., increasing capital stock if thermoelectric power plants are needed) in a state and its neighbors.

The change in the "Exogenous Final Demand (amount)" variable for the utilities sector in state *i* and year *t* is calculated as

$$\Delta D_t^i = \$138.13 * (HP_t^i - 1) * X_{HP}^i$$

where

HP_t^i = the fraction of normal hydroelectric power production in state *i* and year *t* and

X_{HP}^i = the total hydroelectric power production, in MWh, in the state in 2007 (EIA 2009).

B.5 Modeling Impacts to Industry and Mining

Of all the major sectors of water withdrawal for the United States, industry is the smallest (5% of all water withdrawals) after thermoelectric power (48%), irrigation of agriculture (34%), and public water supplies (11%) (Hutson et al. 2004). Mining, whose water availability is modeled separately from the aggregate of other industries, consumes less than 1% of all water.

[27] LAZARD (2008) and a transmission and distribution cost of \$20/MWh (Northwest Power and Conservation Council [2009]).

B.5.1 Modeling Assumptions

A USGS report (Hutson et al. 2004) provides information about aggregate withdrawals of water for all industries and mining but does not break down the numbers by specific industry or provide data on how much water is consumed (e.g., evaporated or incorporated into a product) or returned to its source, such as with once-through cooling. Statistics Canada (2005a), on the other hand, provides a large number of tables with a large breadth of data based on surveys of industrial and mining users of water. We assume that the water use of Canadian industries mirrors that of U.S. industries, proportionally. This assumption is reasonable because the two countries use similar technologies, and the industries are both classified according to the North American Industry Classification System (NAICS). (Because temperatures in the United States are generally warmer than in Canada, it is possible that more U.S. industrial water is used for cooling. In the bullets below [beginning with "Food"], a greater amount of cooling means that there are more opportunities for cutting back the amount of water used by converting to dry cooling. Thus assuming that the United States and Canada use the same proportions for cooling is a conservative approach.)

Hutson et al. (2004) state that food, paper, chemicals, refined petroleum, and primary metals are the largest industrial users of water, and these researchers provide separate data for the mining industry. The Statistics Canada (2005a) survey reports similar findings but also includes the beverage and tobacco manufacturing sector as a significant consumer of water. These six industries account for 87% of all industrial (nonmining) consumption of water. We have focused on these industries.

The data from the hydrological model used in this study give the percentage of normal consumption that can be provided by water supplies. Therefore, we assume there is plenty of water to withdraw, but only a limited amount of this water can be consumed. The remainder of the water must be treated and returned to water supplies where it can be withdrawn and ultimately consumed by other users.

A summary of pertinent statistics for the Statistics Canada survey is provided in Table B-4. Only 13.5% of water intake is actually consumed. The remainder of the water is for the following:

- **Food.** Disclosure problems make it difficult to see clearly what is happening in the data. It is likely that a large portion of the food industry's water consumption is used for sanitary service, most likely in the animal-processing industries. This water is probably relatively difficult to conserve, but it can be treated or transferred to irrigation use. Surface discharge is very small, probably because it is difficult to treat. It is likely that most of the discharge becomes irrigation water. (The italicized values in Table B-4 indicate undisclosed data that we input by assuming that 29% of water intake is used for cooling, as it is in the beverage and tobacco industry.)

- **Beverage and Tobacco.** This industry's consumption rate is the highest of all at 51%. The high percentage is likely due to the fact that water composes the majority of most beverages.

- **Paper.** This industry's consumption rate is only 5%, and it discharges 89% of its intake to the surface, and it spends a lot of money doing these activities. There is very little this industry can do to conserve because it consumes so little and is already spending a lot to treat water.

- **Petroleum and Coal.** This industry is based on transforming petroleum and coal into usable products (i.e., the industry does not include extraction). The industry has a consumption rate of 12%. Much of this is likely due to evaporation, as 87% of the water is used for cooling, condensing, and steam. The 12% could be conserved using similar technologies to those identified for electricity generation.

- **Chemicals.** This industry consumes a relatively high amount of water, probably because the water is used in chemical reactions or as a solute. There is no conservation opportunity with this use of water. Because a large portion of water is used for cooling, condensing, and steam (80%), there are opportunities to conserve water here by using similar technologies to those identified for electricity generation.

- **Primary Metals.** Primary metals manufacturing uses a moderate amount of water in cooling, condensing, and steam (hence there are moderate conservation opportunities) and returns a relatively large percentage of water (80%) in surface discharge.

- **Mining.** Statistics Canada surveys only the mining (except oil and gas) sector. Surface discharge is 98% of withdrawals. Consumption is –37% because mining often "generates" water when mines are below the water table. If the intake is adjusted by adding mine water, the total intake is 674.9 million cubic meters (mil m^3) of water per year and 7% of that amount is consumption. The recycling rate is 448%, meaning that the same water is used over and over again. Since mining consumes so little water and already has a high recycling rate, there are few conservation opportunities.

The USGS study of water use in the United States, i.e., Hutson et al. (2004), includes oil and gas in its mining data. These data are much more limited than the Canadian data and cover only a subset of states. The data report that mining uses 2,250 thousand acre-feet per year of fresh water and 1,660 thousand acre-feet of saline water. Of the saline water, 1,260 thousand acre-feet per year is ground water.

Table B-4. Industrial Use of Water in Canada[28]

	Food	Beverage/ Tobacco	Paper	Petroleum and Coal	Chemicals	Primary Metals	Mining	Mining (adjusted)
Intake (mil m^3)	1366.8	160.6	2598.3	364.8	532.5	1606.2	458.9	674.9
Consumption (mil m3)	272.7	81.3	134.3	42.3	149.9	238.4	-171.7	44.3
Consumption Rate	20%	51%	5%	12%	28%	15%	-37%	7%
Process Water	869.4	-	1800.4	42.5	92	518.8	376.7	376.7
% Intake	64%	-	69%	12%	17%	32%	82%	56%
% Cons.	319%	-	1341%	100%	61%	218%	-219%	850%
Cooling, Condensing, Steam	*394.0*	46.3	731.9	317.5	423.4	839.6	37.7	37.7
% Intake	*29%*	29%	28%	87%	80%	52%	8%	6%
% Cons.	*144%*	57%	545%	751%	282%	352%	-22%	85%

[28] Data from Statistics Canada (2005a).

Information about the output of Canadian industries is included in Table B-5. We assume that U.S. industries use water at the same rate, per amount of output, as Canadian industries (i.e., the right column of Table B-5 is representative of U.S. industries). Due to a lack of information about water use in oil and gas extraction, we assume that the industry has the same water-use characteristics as the mining (except oil and gas) sector.

To calculate the costs of retrofitting cooling systems to dry-cooling systems, we assume that the costs per amount of water consumption saved are the same as in the electric power industry. We assume that the maximum percentage of water that can be conserved by retrofitting cooling systems in each industry is equal to the amount of water used in cooling divided by the total intake. This value ranges from 6% for mining to 87% for petrochemicals and coal. Again, we assume a value of the previously mentioned $4.95 m^3$/MWh for the amount of water used by thermoelectric plants for evaporative cooling (Yang and Dziegielewski 2007), and we use the previous value for retrofitting power generation plants of \$18.13/MWh. Dividing \$18.13/MWh by $4.95 m^3$/MWh equals an additional cost of \$3.66/m^3 for water saved by retrofitting to dry cooling.[29]

We use the previous value of investment necessary to retrofit power generation plants of \$71.35/MWh. Dividing this value by $4.95 m^3$/MWh equals an investment cost of \$14.41/m^3 for water conserved by retrofitting to dry cooling. As with electric power, any cooling retrofits that occur will reduce the industrial requirements for water in future years.

We assume that once the maximum amount of water has been conserved by retrofitting to dry cooling, additional water is not easily conserved because it often goes into production or is otherwise lost in the production process. Water must be obtained through desalination, or otherwise firms must shut down production to conserve any remaining water. Desalination is available to firms in states that are adjacent to an ocean at an increased cost of \$1.62/m^3 (for the reasons noted previously). Because the increased cost of using desalinated water is much cheaper than the increased cost of retrofitting to dry cooling, we assume that firms will use desalinated water to adjust to the shortfall in water. Firms in all industries conserve water in the same proportion (e.g., if the available water is a fraction I_t^i of normal demand, all firms have access to that fraction.)

In states not adjacent to an ocean, we assume that all industries initially retrofit cooling systems to conserve water. For simplification purposes, industries retrofit according to a linear function that is proportional to the industry's consumption of water for cooling purposes multiplied by the water shortfall.[30] Once all retrofits have been performed, if the retrofits have not conserved enough water, industries shut down in equal proportions. This is a conservative assumption because industries are likely to shut down according to how intensively they use water for noncooling purposes (based upon

[29] This amount is slightly more expensive than the \$1.62/m^3 increase for desalinated water used previously. Thus, it may be slightly cheaper for a wet closed-loop cooling system to use desalinated water rather than to retrofit the system. However, the cooling in these data is an aggregate of both wet closed-loop and once-through types.

[30] The implication of this assumption is that different industries will conserve water at different rates depending upon the intensity at which the industries consume water for cooling.

water consumption per dollar of output), with the most intensive industries shutting down first. Calculations of these intensities are given in Table B-5.

Table B-5. Noncooling Consumption Rates Compared with Industry Output

	Noncooling Consumption (mil m^3) [31]	2005 Output $CAN mil (2002) [32]	Output in $US mil (2008) [33]	Noncooling Consumption m^3/$M US Output
Food Manufacturing	194.1	$71,028	$102,330	1,897
Beverage and Tobacco Product Manufacturing	57.9	$13,901	$20,027	2,889
Paper Manufacturing	96.5	$33,546	$48,330	1,996
Petroleum and Coal Product Manufacturing	5.5	$59,228	$85,330	64
Chemical Manufacturing	30.7	$54,659	$78,747	390
Primary Metal Manufacturing	113.8	$49,790	$71,733	1,586

Table B-6 provides the water use by industry based on Canadian statistics. Column one gives the percentage of water intake that is used for cooling, column two gives the total amount of water consumed by each industry in 2005 on an annual basis, and columns three and four list the value of economic output from each industry in Canadian and U.S. dollars, respectively. Column five lists the resulting consumption rate in terms of water volume per unit of economic activity.

[31] Statistics Canada (2005a).
[32] Statistics Canada (2005b).
[33] Converted to 2005 Canadian dollars by multiplying by 1.099 (112.27/102.13) (NationalMaster), converted to 2005 USD by multiplying by 1.21 (2005 exchange rate and PPP equivalence (International Comparison Project [2008]) and converted by 2008 USD by multiplying by 1.08 (122.422/113.026, EconStats).

Table B-6. Total Consumption[34]

	Cooling % Intake	Consumption (mil m^3)	2005 Output $CAN mil (2002)	Output in $US mil (2008)	Consumption m^3/$M US output
Food Manufacturing	29%	272.7	$71,028	$102,330	2,665
Beverage and Tobacco Product Manufacturing	29%	81.3	$13,901	$20,027	4,059
Paper Manufacturing	28%	134.3	$33,546	$48,330	2,779
Petroleum and Coal Product Manufacturing	87%	42.3	$59,228	$85,330	496
Chemical Manufacturing	80%	149.9	$54,659	$78,747	1,904
Primary Metal Manufacturing	52%	238.4	$49,790	$71,733	3,323
Mining (adjusted)	6%	44.3	$24,351	$35,083	1,263

B.5.2 Modeling Procedures

The following sections outline the equations used to determine the impacts from water shortages in industry, using the assumptions generated in Section B.5.1.

B.5.2.1 States not Adjacent to an Ocean

These states first retrofit industrial cooling systems to conserve water. If additional water conservation is necessary, industries must halt some production. For each state *i* and year *t*, a fraction of water consumption that can be saved through dry-cooling retrofits is calculated by weighting each industry's cooling-water intake as follows, using data from Table B-6, presented previously, and the REMI model's standard regional control outputs:

[34] Based on calculations in Tables B-4 and B-5.

$$\overline{\%c}_t^i = \frac{\%c_f WI_f Y_{f,t}^i + \%c_b WI_b Y_{b,t}^i + \%c_p WI_p Y_{p,t}^i + \%c_e WI_e Y_{e,t}^i + \%c_c WI_c Y_{c,t}^i + \%c_m WI_m Y_{m,t}^i}{WI_f Y_{f,t}^i + WI_b Y_{b,t}^i + WI_p Y_{p,t}^i + WI_e Y_{e,t}^i + WI_c Y_{c,t}^i + WI_m Y_{m,t}^i},$$

where

f, b, p, e, c, and *m* represent the six nonmining industries,

$\%c_x$ = the percentage of consumption assumed to be used in cooling,

WI_x = the water intensity of each industry, and

$Y_{x,t}^i$ = the output of industry *x* (in millions of 2008$ US, from the REMI model's standard regional control).

Because mining is disaggregated from data in the Sandia hydrological model, its value is simply 6%.

Production costs in each industry increase by[35]

$$\Delta PC_{x,t}^i = \begin{cases} (1-I_t^i)/\overline{\%c}_t^i * \$3.66 * \%c_x WI_x Y_{x,t}^i & \Big| (1-I_t^i) < \overline{\%c}_t^i \\ \$3.66 * \%c_x WI_x Y_{x,t}^i & \Big| (1-I_t^i) \geq \overline{\%c}_t^i \end{cases},$$

where

I_t^i = the fraction of usual water demanded that is available to all industries.

For mining, which includes both the mining (except oil and gas) sector and the oil and gas extraction sector, this equation simplifies to

$$\Delta PC_{m,t}^i = \begin{cases} (1-M_t^i)/0.06 * \$3.66 * 0.06 * 1263 Y_{m,t}^i & \Big| (1-M_t^i) < 0.06 \\ \$3.66 * 0.06 * 1263 Y_{m,t}^i & \Big| (1-M_t^i) \geq 0.06 \end{cases},$$

where

M_t^i = the fraction of usual water demanded that is available to mining.

Increases in production costs, $\Delta PC_{x,t}^i$, are inputs into the REMI model that exogenously increase the "Production Cost (amount)" variable for the appropriate

[35] The vertical line at the end of each equation given in this section notes the domain of the independent variable for which the equation is applicable.

industries. Investment in cooling-system retrofits are made until all industrial cooling systems have been retrofitted (i.e., $\overline{\%c}_t^i$ has been conserved. Investment is based upon previous retrofits in the following sets of equations:

$$\Delta IN_{x,t}^i = \begin{cases} (I_{t-1}^i - I_t^i) * \$14.41 * \%c_x WI_x Y_{x,t}^i & (1 - I_{t-1}^i) \le (1 - I_t^i) < \overline{\%c}_t^i \\ [I_{t-1}^i - (1 - \overline{\%c}_t^i)] * \$14.41 * \%c_x WI_x Y_{x,t}^i & (1 - I_{t-1}^i) < \overline{\%c}_t^i < (1 - I_t^i) \\ 0 & otherwise \end{cases}$$

and for mining:

$$\Delta IN_{m,t}^i = \begin{cases} (M_{t-1}^i - M_t^i) * \$14.41 * 0.06 * 1263 Y_{x,t}^i & (1 - M_{t-1}^i) \le (1 - M_t^i) < 0.06 \\ [M_{t-1}^i - (1 - 0.06)] * \$14.41 * 0.06 * 1263 Y_{x,t}^i & (1 - M_{t-1}^i) < 0.06 < (1 - M_t^i) \\ 0 & otherwise \end{cases}.$$

The first case occurs when water availability is lower than the previous year but still higher than the maximum amount that can be conserved with cooling retrofits. The second case occurs when water availability is lower than the previous year and lower than the maximum that can be conserved with cooling system retrofits. The third case occurs when water availability increases or decreases further below the maximum retrofitting conservation amount. Because the industry can operate with less water every year to the point where all possible retrofits have been made,

$$I_t^i \le \max\left(I_{t-1}^i, (1 - \overline{\%c}_t^i)\right)$$

and

$$M_t^i \le \max\left(M_{t-1}^i, (1 - 0.06)\right).$$

As with investments for dry-cooling retrofits for electric power generation, we assume that two-thirds of $\Delta IN_{x,t}^i$ goes to the machinery manufacturing sector and one-third goes to the electrical equipment and appliance manufacturing sector by modifying the “Exogenous Final Demand (amount)” variable.

When water availability is below the level that can satisfy industry needs through cooling-system retrofits (e.g., $(1 - I_t^i) > \overline{\%c}_t^i$), firms must shut down some portion of production to conserve water. We assume that firms reduce their output in proportion to the amount that the water shortage exceeds the level that can be conserved with cooling system conservation. This can be represented as

$$\Delta Y_{x,t}^{i} = -(1 - I_t^i - \overline{\%c}_t^i)/(1 - \overline{\%c}_t^i) Y_{x,t}^i \Big| (1 - I_t^i) > \overline{\%c}_t^i .$$

For mining, the equation simplifies to

$$\Delta Y_{m,t}^{i} = -(1 - M_t^i - 0.06)/(1 - 0.06) Y_{m,t}^i \Big| (1 - M_t^i) > 0.06.$$

This change in industry output is treated in the REMI model as a change to the "Industry Behavior" component of the model through exogenously reducing "Industry Sales/Exogenous Production" in the model by an amount equaling $\Delta Y_{x,t}^i$. An alternative strategy is to adjust "Firm Sales" by changing "Firm Behavior," In the REMI model "Firm Behavior" is represented by a set of input adjustment parameters that allow "displacement [of production by local industries] due to competition in the local and nearby markets and the national market," whereas changes to what REMI calls "Industry Behavior" leads to an exogenous change in the production of local industries that will not be compensated for by other firms increasing their production levels. Although it is likely that firms in regions of the country with abundant water increase production to take up the slack created by water shortages, the REMI model does not include explicitly consider water availability. Because many of the firms picking up the slack in a REMI simulation would be within the same region, using "Firm Behavior" would result in unrealistically high levels of production as a result of water shortages. Thus, choosing "Industry Behavior" is the more suitable assumption.

B.5.2.2 States Adjacent to an Ocean

The hydrological model first attempts to purchase water rights to mitigate the impact or reduce regional water availability. Once this option is exhausted, these states conserve water by purchasing desalinated water with a cost of $1.62/m^3 for water conserved. The increase in production costs for each industry is based upon the industry's water intensity for water consumption and the industry's output, as represented by $\Delta PC_{x,t}^i = \$1.62 * (1 - I_t^i) * WI_x Y_{x,t}^i$. This equation assumes that each industry loses the same fraction $(1 - I_t^i)$ of its normal water demanded. The whole amount of the change in production costs is applied as increased production costs for industry *x*, and a fraction of the amount, $\overline{\%c}_t^i$, is applied to increased production in the utility industry to correspond to increased production of desalinated water.

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Appendix C. Base-Case Normalization

Even in the absence of climate change, economic and population growth will lead to potential water shortages (EPA 2002; GAO 2003; Karl et al. 2009). The impacts from these water constraints are typically not considered within macroeconomic forecasts and are not included in the base-case REMI forecast used as the macroeconomic referent in the analysis presented in the body of this report.

The study uses the concept of water availability, which compares indicated demand with expected supply. If there is no change in usage behaviors, the macroeconomic referent would produce reduced water availability in the future. In reality, if there were constraints of water availability, industries and consumers would more efficiently use water to maintain operations. The analysis of the main text only includes differences in water availability beyond what are considered in the hydrological referent. We call this a normalization, where the implied (lack of) water availability in the referent is disregarded and only additional changes due to climate change are associated with macroeconomic impacts.

To present a more complete picture, this appendix presents the impacts of water constraints that are not due to climate change. The color-coded tables, organized by year and state, note the water availability for municipal utilities, industry, and thermoelectric facilities (Figure C-1) and for mining (Figure C-2). The estimated impacts that would occur for the GDP and for employment follow in Figure C-3, Figure C-4, and Table C-1. For all the tables and figures in this appendix, note that precipitation and thus hydrology is assumed constant over the entire time period. The change in water availability is solely due to the demand exceeding a constant supply.

In Figures C-1 and C-2 shown first, a water availability value of 1.0, depicted as green, indicates that all the water needed is available. As demand starts to exceed supply, a value less than 1.0 is present, and the color starts to turn yellow. When there is a significant gap between supply and demand, the numerical value diminishes further as yellow turns to red. Several states, including South Carolina, Tennessee, Virginia, and West Virginia, may experience rather severe water constraints even in the absence of climate change.

Year	AL	AZ	AR	CA	CO	CT	DE	DC	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
2010	1.000	0.997	1.000	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	0.995	1.000	0.998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.992	1.000	0.998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2013	1.000	0.990	1.000	0.997	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2014	1.000	0.988	1.000	0.996	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	1.000	0.985	1.000	0.996	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2016	1.000	0.983	1.000	0.995	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2017	1.000	0.980	1.000	0.995	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2018	1.000	0.978	1.000	0.994	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2019	1.000	0.976	1.000	0.993	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.000	0.973	1.000	0.993	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2021	1.000	0.971	1.000	0.992	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2022	1.000	0.968	1.000	0.991	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2023	1.000	0.966	1.000	0.991	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2024	1.000	0.963	1.000	0.990	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000
2025	1.000	0.961	1.000	0.989	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.989	1.000	1.000	1.000	1.000	1.000
2026	1.000	0.958	1.000	0.988	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.978	1.000	1.000	1.000	1.000	1.000
2027	1.000	0.955	1.000	0.988	1.000	0.998	0.997	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.968	1.000	1.000	1.000	1.000	1.000
2028	1.000	0.952	1.000	0.987	1.000	0.989	0.987	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.957	1.000	1.000	1.000	1.000	1.000
2029	1.000	0.950	1.000	0.986	1.000	0.979	0.978	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.946	1.000	1.000	1.000	1.000	1.000
2030	1.000	0.947	1.000	0.985	1.000	0.970	0.968	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.935	1.000	1.000	1.000	1.000	1.000
2031	1.000	0.943	1.000	0.984	1.000	0.961	0.959	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.924	1.000	1.000	1.000	1.000	1.000
2032	1.000	0.940	1.000	0.983	1.000	0.953	0.949	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.913	1.000	1.000	1.000	1.000	1.000
2033	1.000	0.937	1.000	0.982	1.000	0.944	0.939	1.000	1.000	0.998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.902	1.000	1.000	1.000	1.000	1.000
2034	1.000	0.933	1.000	0.981	1.000	0.936	0.929	1.000	1.000	0.990	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.892	1.000	1.000	1.000	1.000	1.000
2035	1.000	0.930	1.000	0.980	1.000	0.928	0.920	1.000	1.000	0.983	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.881	1.000	1.000	1.000	1.000	1.000
2036	1.000	0.926	1.000	0.979	1.000	0.921	0.910	1.000	1.000	0.976	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.870	1.000	1.000	1.000	1.000	1.000
2037	1.000	0.923	1.000	0.978	1.000	0.914	0.900	1.000	1.000	0.968	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.860	1.000	1.000	1.000	1.000	1.000
2038	1.000	0.919	1.000	0.977	1.000	0.907	0.890	1.000	1.000	0.961	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.850	1.000	1.000	1.000	1.000	1.000
2039	0.987	0.915	1.000	0.976	1.000	0.901	0.880	1.000	1.000	0.953	1.000	1.000	0.987	1.000	1.000	1.000	1.000	1.000	1.000	0.839	1.000	1.000	1.000	1.000	1.000
2040	0.971	0.911	1.000	0.974	1.000	0.894	0.870	1.000	1.000	0.946	1.000	1.000	0.968	1.000	1.000	1.000	1.000	1.000	1.000	0.829	1.000	1.000	1.000	1.000	1.000
2041	0.955	0.907	1.000	0.973	1.000	0.889	0.860	1.000	1.000	0.939	1.000	1.000	0.950	1.000	1.000	1.000	1.000	1.000	1.000	0.819	1.000	1.000	1.000	1.000	1.000
2042	0.940	0.902	1.000	0.972	1.000	0.883	0.851	1.000	1.000	0.932	1.000	1.000	0.932	1.000	1.000	1.000	1.000	1.000	1.000	0.810	1.000	1.000	1.000	1.000	1.000
2043	0.924	0.898	1.000	0.970	1.000	0.878	0.841	1.000	1.000	0.925	1.000	1.000	0.915	1.000	1.000	1.000	1.000	1.000	1.000	0.800	1.000	1.000	1.000	1.000	1.000
2044	0.908	0.894	1.000	0.969	1.000	0.873	0.831	1.000	1.000	0.918	1.000	1.000	0.897	1.000	1.000	1.000	1.000	1.000	1.000	0.791	0.984	1.000	1.000	1.000	1.000
2045	0.893	0.889	1.000	0.967	1.000	0.869	0.822	1.000	1.000	0.911	1.000	1.000	0.880	0.991	1.000	1.000	1.000	1.000	1.000	0.781	0.968	1.000	1.000	1.000	1.000
2046	0.878	0.885	1.000	0.966	1.000	0.864	0.812	1.000	1.000	0.905	1.000	1.000	0.864	0.978	1.000	1.000	1.000	1.000	1.000	0.772	0.952	1.000	1.000	1.000	1.000
2047	0.864	0.880	1.000	0.964	1.000	0.860	0.802	1.000	1.000	0.898	1.000	1.000	0.847	0.964	1.000	1.000	1.000	1.000	1.000	0.762	0.937	1.000	1.000	1.000	1.000
2048	0.849	0.876	1.000	0.962	1.000	0.855	0.793	1.000	1.000	0.892	1.000	1.000	0.831	0.950	1.000	1.000	1.000	0.993	1.000	0.753	0.921	1.000	1.000	1.000	1.000
2049	0.835	0.871	1.000	0.960	1.000	0.851	0.783	1.000	0.998	0.885	1.000	1.000	0.816	0.937	1.000	0.990	1.000	0.982	1.000	0.744	0.905	1.000	1.000	1.000	1.000
2050	0.821	0.866	1.000	0.958	1.000	0.846	0.773	1.000	0.994	0.879	1.000	1.000	0.800	0.924	1.000	0.978	1.000	0.971	1.000	0.734	0.890	1.000	1.000	1.000	1.000

Year	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
2010	1.000	0.991	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	0.987	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.984	1.000	1.000	0.998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2013	1.000	0.981	1.000	1.000	0.997	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2014	1.000	0.978	1.000	1.000	0.997	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	1.000	0.975	1.000	1.000	0.996	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2016	1.000	0.972	1.000	1.000	0.995	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2017	1.000	0.969	1.000	1.000	0.994	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2018	1.000	0.965	1.000	1.000	0.994	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2019	1.000	0.962	1.000	1.000	0.993	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000
2020	1.000	0.959	1.000	1.000	0.992	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.986	1.000	1.000	1.000	1.000	1.000	0.982	1.000	1.000	1.000	1.000
2021	1.000	0.956	1.000	1.000	0.991	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.968	1.000	1.000	1.000	1.000	1.000	0.965	1.000	1.000	1.000	1.000
2022	1.000	0.953	1.000	1.000	0.991	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.950	1.000	1.000	1.000	1.000	1.000	0.949	1.000	1.000	1.000	1.000
2023	1.000	0.950	1.000	1.000	0.990	1.000	0.997	1.000	1.000	1.000	1.000	1.000	1.000	0.931	1.000	1.000	1.000	1.000	1.000	0.932	1.000	1.000	1.000	1.000
2024	1.000	0.947	1.000	1.000	0.989	1.000	0.986	1.000	1.000	1.000	1.000	1.000	1.000	0.913	1.000	1.000	1.000	1.000	1.000	0.916	1.000	1.000	1.000	1.000
2025	1.000	0.944	1.000	1.000	0.988	1.000	0.975	1.000	1.000	1.000	1.000	1.000	1.000	0.896	1.000	1.000	1.000	1.000	1.000	0.900	1.000	1.000	1.000	1.000
2026	1.000	0.941	1.000	1.000	0.988	1.000	0.964	1.000	1.000	1.000	1.000	1.000	1.000	0.878	1.000	1.000	1.000	1.000	1.000	0.884	1.000	1.000	1.000	1.000
2027	1.000	0.938	1.000	1.000	0.987	1.000	0.953	1.000	1.000	1.000	1.000	1.000	1.000	0.861	1.000	1.000	1.000	1.000	1.000	0.868	1.000	1.000	1.000	1.000
2028	1.000	0.935	1.000	1.000	0.986	1.000	0.941	1.000	1.000	1.000	1.000	1.000	1.000	0.843	1.000	1.000	1.000	1.000	1.000	0.853	1.000	1.000	1.000	1.000
2029	1.000	0.932	1.000	1.000	0.985	1.000	0.930	1.000	1.000	1.000	1.000	1.000	1.000	0.826	1.000	0.980	1.000	1.000	1.000	0.837	1.000	1.000	1.000	1.000
2030	1.000	0.929	1.000	1.000	0.984	1.000	0.918	1.000	1.000	1.000	1.000	1.000	1.000	0.808	1.000	0.957	1.000	1.000	1.000	0.822	1.000	1.000	1.000	1.000
2031	1.000	0.926	1.000	1.000	0.983	1.000	0.906	1.000	1.000	1.000	1.000	1.000	1.000	0.791	1.000	0.933	1.000	1.000	1.000	0.807	1.000	1.000	1.000	1.000
2032	1.000	0.923	1.000	1.000	0.982	1.000	0.894	1.000	1.000	1.000	1.000	1.000	1.000	0.773	1.000	0.909	1.000	1.000	1.000	0.792	1.000	1.000	1.000	1.000
2033	1.000	0.920	1.000	1.000	0.981	1.000	0.881	1.000	1.000	1.000	1.000	1.000	0.994	0.756	1.000	0.886	1.000	1.000	1.000	0.778	1.000	1.000	1.000	1.000
2034	1.000	0.916	0.987	1.000	0.980	0.997	0.869	1.000	1.000	1.000	1.000	0.984	0.985	0.739	1.000	0.863	1.000	1.000	1.000	0.763	1.000	1.000	1.000	1.000
2035	1.000	0.913	0.970	1.000	0.979	0.979	0.857	1.000	1.000	1.000	1.000	0.964	0.978	0.723	1.000	0.841	1.000	1.000	1.000	0.750	1.000	1.000	1.000	1.000
2036	1.000	0.910	0.952	1.000	0.978	0.962	0.844	1.000	1.000	1.000	1.000	0.943	0.970	0.706	1.000	0.819	1.000	1.000	1.000	0.736	1.000	0.980	1.000	1.000
2037	1.000	0.906	0.935	1.000	0.977	0.945	0.832	1.000	1.000	1.000	1.000	0.923	0.962	0.690	1.000	0.797	1.000	1.000	1.000	0.723	1.000	0.956	1.000	1.000
2038	1.000	0.903	0.918	1.000	0.976	0.929	0.819	1.000	1.000	1.000	1.000	0.904	0.954	0.674	1.000	0.776	1.000	1.000	1.000	0.710	1.000	0.933	1.000	1.000
2039	1.000	0.899	0.901	1.000	0.975	0.913	0.806	1.000	1.000	1.000	1.000	0.886	0.946	0.658	1.000	0.756	1.000	1.000	1.000	0.698	1.000	0.910	1.000	1.000
2040	1.000	0.896	0.885	1.000	0.974	0.898	0.794	1.000	1.000	1.000	1.000	0.868	0.939	0.643	1.000	0.736	1.000	1.000	1.000	0.686	1.000	0.888	1.000	1.000
2041	1.000	0.892	0.869	1.000	0.973	0.883	0.782	1.000	1.000	1.000	1.000	0.851	0.931	0.628	1.000	0.717	1.000	1.000	0.988	0.675	1.000	0.866	1.000	1.000
2042	1.000	0.889	0.853	1.000	0.972	0.869	0.770	1.000	0.994	1.000	1.000	0.835	0.924	0.614	1.000	0.698	1.000	1.000	0.974	0.664	1.000	0.845	1.000	1.000
2043	1.000	0.885	0.837	1.000	0.970	0.854	0.758	1.000	0.977	1.000	1.000	0.819	0.917	0.600	1.000	0.680	1.000	1.000	0.960	0.654	1.000	0.825	1.000	1.000
2044	1.000	0.882	0.821	1.000	0.969	0.841	0.747	1.000	0.961	1.000	1.000	0.804	0.909	0.587	1.000	0.663	1.000	1.000	0.947	0.643	1.000	0.805	1.000	1.000
2045	1.000	0.878	0.806	1.000	0.968	0.827	0.735	1.000	0.945	1.000	1.000	0.789	0.902	0.573	1.000	0.646	1.000	1.000	0.934	0.634	1.000	0.785	1.000	1.000
2046	1.000	0.875	0.791	0.997	0.966	0.814	0.724	1.000	0.930	1.000	1.000	0.775	0.895	0.561	1.000	0.629	1.000	1.000	0.920	0.624	1.000	0.766	1.000	1.000
2047	1.000	0.871	0.775	0.988	0.965	0.802	0.713	1.000	0.914	1.000	1.000	0.761	0.888	0.548	1.000	0.613	1.000	1.000	0.907	0.615	1.000	0.748	1.000	1.000
2048	1.000	0.868	0.760	0.979	0.964	0.789	0.702	1.000	0.899	1.000	1.000	0.748	0.881	0.536	1.000	0.598	1.000	1.000	0.894	0.606	1.000	0.730	1.000	1.000
2049	1.000	0.864	0.745	0.970	0.962	0.776	0.690	1.000	0.884	1.000	1.000	0.734	0.873	0.524	1.000	0.583	1.000	1.000	0.881	0.598	1.000	0.713	0.994	1.000
2050	1.000	0.860	0.730	0.961	0.961	0.764	0.679	1.000	0.869	1.000	1.000	0.721	0.866	0.512	1.000	0.568	1.000	1.000	0.868	0.589	1.000	0.696	0.980	1.000

Figure C-1. Municipal, industry, and thermoelectric water availability in the hydrological referent.

Year	AL	AZ	AR	CA	CO	CT	DE	DC	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
2010	1.000	0.994	1.000	0.997	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	0.989	1.000	0.996	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.985	1.000	0.995	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2013	1.000	0.980	1.000	0.994	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2014	1.000	0.975	1.000	0.993	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	1.000	0.970	1.000	0.992	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2016	1.000	0.966	1.000	0.990	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2017	1.000	0.961	1.000	0.989	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2018	1.000	0.956	1.000	0.988	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2019	1.000	0.951	1.000	0.986	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2020	1.000	0.946	1.000	0.985	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2021	1.000	0.941	1.000	0.984	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2022	1.000	0.937	1.000	0.983	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2023	1.000	0.932	1.000	0.981	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2024	1.000	0.927	1.000	0.980	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000
2025	1.000	0.922	1.000	0.978	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.978	1.000	1.000	1.000	1.000	1.000
2026	1.000	0.916	1.000	0.977	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.957	1.000	1.000	1.000	1.000	1.000
2027	1.000	0.911	1.000	0.975	1.000	0.996	0.993	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.935	1.000	1.000	1.000	1.000	1.000
2028	1.000	0.905	1.000	0.974	1.000	0.977	0.975	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.914	1.000	1.000	1.000	1.000	1.000
2029	1.000	0.899	1.000	0.972	1.000	0.959	0.956	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.892	1.000	1.000	1.000	1.000	1.000
2030	1.000	0.893	1.000	0.970	1.000	0.941	0.937	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.870	1.000	1.000	1.000	1.000	1.000
2031	1.000	0.887	1.000	0.968	1.000	0.923	0.918	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.849	1.000	1.000	1.000	1.000	1.000
2032	1.000	0.880	1.000	0.967	1.000	0.905	0.898	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.827	1.000	1.000	1.000	1.000	1.000
2033	1.000	0.874	1.000	0.965	1.000	0.888	0.878	1.000	1.000	0.995	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.805	1.000	1.000	1.000	1.000	1.000
2034	1.000	0.867	1.000	0.963	1.000	0.872	0.859	1.000	1.000	0.981	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.783	1.000	1.000	1.000	1.000	1.000
2035	1.000	0.860	1.000	0.960	1.000	0.856	0.839	1.000	1.000	0.966	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.762	1.000	1.000	1.000	1.000	1.000
2036	1.000	0.853	1.000	0.958	1.000	0.842	0.819	1.000	1.000	0.951	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.741	1.000	1.000	1.000	1.000	1.000
2037	1.000	0.845	1.000	0.956	1.000	0.827	0.799	1.000	1.000	0.937	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.720	1.000	1.000	1.000	1.000	1.000
2038	1.000	0.837	1.000	0.954	1.000	0.814	0.779	1.000	1.000	0.922	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.699	1.000	1.000	1.000	1.000	1.000
2039	0.975	0.830	1.000	0.951	1.000	0.801	0.760	1.000	1.000	0.907	1.000	1.000	0.974	1.000	1.000	1.000	1.000	1.000	1.000	0.679	1.000	1.000	1.000	1.000	1.000
2040	0.942	0.821	1.000	0.949	1.000	0.789	0.740	1.000	1.000	0.892	1.000	1.000	0.936	1.000	1.000	1.000	1.000	1.000	1.000	0.659	1.000	1.000	1.000	1.000	1.000
2041	0.910	0.813	1.000	0.946	1.000	0.777	0.721	1.000	1.000	0.878	1.000	1.000	0.900	1.000	1.000	1.000	1.000	1.000	1.000	0.639	1.000	1.000	1.000	1.000	1.000
2042	0.879	0.805	1.000	0.943	1.000	0.767	0.701	1.000	1.000	0.864	1.000	1.000	0.864	1.000	1.000	1.000	1.000	1.000	1.000	0.619	1.000	1.000	1.000	1.000	1.000
2043	0.848	0.796	1.000	0.940	1.000	0.756	0.682	1.000	1.000	0.850	1.000	1.000	0.829	1.000	1.000	1.000	1.000	1.000	1.000	0.600	0.999	1.000	1.000	1.000	1.000
2044	0.817	0.788	1.000	0.937	1.000	0.747	0.663	1.000	1.000	0.836	1.000	1.000	0.794	1.000	1.000	1.000	1.000	1.000	1.000	0.581	0.967	1.000	1.000	1.000	1.000
2045	0.787	0.779	1.000	0.934	1.000	0.737	0.643	1.000	1.000	0.823	1.000	1.000	0.761	0.982	1.000	1.000	1.000	1.000	1.000	0.562	0.936	1.000	1.000	1.000	1.000
2046	0.757	0.770	1.000	0.931	1.000	0.728	0.624	1.000	1.000	0.809	1.000	1.000	0.728	0.955	1.000	1.000	1.000	1.000	1.000	0.544	0.905	1.000	1.000	1.000	1.000
2047	0.728	0.761	1.000	0.928	1.000	0.719	0.605	1.000	1.000	0.796	1.000	1.000	0.695	0.928	1.000	1.000	1.000	1.000	1.000	0.525	0.873	1.000	1.000	1.000	1.000
2048	0.699	0.751	1.000	0.924	1.000	0.710	0.586	1.000	1.000	0.783	1.000	1.000	0.663	0.901	1.000	1.000	1.000	0.987	1.000	0.506	0.842	1.000	1.000	1.000	1.000
2049	0.670	0.742	1.000	0.921	1.000	0.702	0.566	1.000	0.995	0.770	1.000	1.000	0.631	0.874	1.000	0.980	1.000	0.964	1.000	0.487	0.811	1.000	1.000	1.000	1.000
2050	0.642	0.732	1.000	0.917	1.000	0.693	0.546	1.000	0.989	0.758	1.000	1.000	0.600	0.848	1.000	0.956	1.000	0.943	1.000	0.469	0.780	1.000	1.000	1.000	1.000

Year	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
2010	1.000	0.981	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2011	1.000	0.975	1.000	1.000	0.997	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2012	1.000	0.968	1.000	1.000	0.996	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2013	1.000	0.962	1.000	1.000	0.995	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2014	1.000	0.955	1.000	1.000	0.993	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2015	1.000	0.949	1.000	1.000	0.992	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2016	1.000	0.943	1.000	1.000	0.990	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2017	1.000	0.937	1.000	1.000	0.989	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2018	1.000	0.931	1.000	1.000	0.987	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2019	1.000	0.925	1.000	1.000	0.986	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.998	1.000	1.000	1.000	1.000
2020	1.000	0.919	1.000	1.000	0.984	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.971	1.000	1.000	1.000	1.000	1.000	0.965	1.000	1.000	1.000	1.000
2021	1.000	0.913	1.000	1.000	0.983	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.935	1.000	1.000	1.000	1.000	1.000	0.931	1.000	1.000	1.000	1.000
2022	1.000	0.907	1.000	1.000	0.981	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.899	1.000	1.000	1.000	1.000	1.000	0.898	1.000	1.000	1.000	1.000
2023	1.000	0.901	1.000	1.000	0.980	1.000	0.994	1.000	1.000	1.000	1.000	1.000	1.000	0.863	1.000	1.000	1.000	1.000	1.000	0.864	1.000	1.000	1.000	1.000
2024	1.000	0.895	1.000	1.000	0.978	1.000	0.972	1.000	1.000	1.000	1.000	1.000	1.000	0.827	1.000	1.000	1.000	1.000	1.000	0.831	1.000	1.000	1.000	1.000
2025	1.000	0.889	1.000	1.000	0.977	1.000	0.951	1.000	1.000	1.000	1.000	1.000	1.000	0.792	1.000	1.000	1.000	1.000	1.000	0.800	1.000	1.000	1.000	1.000
2026	1.000	0.883	1.000	1.000	0.975	1.000	0.928	1.000	1.000	1.000	1.000	1.000	1.000	0.757	1.000	1.000	1.000	1.000	1.000	0.768	1.000	1.000	1.000	1.000
2027	1.000	0.877	1.000	1.000	0.974	1.000	0.906	1.000	1.000	1.000	1.000	1.000	1.000	0.722	1.000	1.000	1.000	1.000	1.000	0.736	1.000	1.000	1.000	1.000
2028	1.000	0.871	1.000	1.000	0.972	1.000	0.883	1.000	1.000	1.000	1.000	1.000	1.000	0.687	1.000	1.000	1.000	1.000	1.000	0.706	1.000	1.000	1.000	1.000
2029	1.000	0.865	1.000	1.000	0.970	1.000	0.859	1.000	1.000	1.000	1.000	1.000	1.000	0.651	1.000	0.961	1.000	1.000	1.000	0.675	1.000	1.000	1.000	1.000
2030	1.000	0.859	1.000	1.000	0.968	1.000	0.836	1.000	1.000	1.000	1.000	1.000	1.000	0.617	1.000	0.914	1.000	1.000	1.000	0.645	1.000	1.000	1.000	1.000
2031	1.000	0.852	1.000	1.000	0.967	1.000	0.812	1.000	1.000	1.000	1.000	1.000	1.000	0.582	1.000	0.865	1.000	1.000	1.000	0.615	1.000	1.000	1.000	1.000
2032	1.000	0.846	1.000	1.000	0.965	1.000	0.787	1.000	1.000	1.000	1.000	1.000	1.000	0.547	1.000	0.818	1.000	1.000	1.000	0.585	1.000	1.000	1.000	1.000
2033	1.000	0.839	1.000	1.000	0.963	1.000	0.763	1.000	1.000	1.000	1.000	1.000	0.987	0.512	1.000	0.772	1.000	1.000	1.000	0.556	1.000	1.000	1.000	1.000
2034	1.000	0.833	0.974	1.000	0.961	0.994	0.738	1.000	1.000	1.000	1.000	0.969	0.971	0.478	1.000	0.726	1.000	1.000	1.000	0.527	1.000	1.000	1.000	1.000
2035	1.000	0.826	0.940	1.000	0.959	0.959	0.713	1.000	1.000	1.000	1.000	0.927	0.955	0.445	1.000	0.682	1.000	1.000	1.000	0.500	1.000	1.000	1.000	1.000
2036	1.000	0.820	0.904	1.000	0.957	0.924	0.688	1.000	1.000	1.000	1.000	0.886	0.939	0.412	1.000	0.638	1.000	1.000	1.000	0.472	1.000	0.960	1.000	1.000
2037	1.000	0.813	0.870	1.000	0.955	0.891	0.663	1.000	1.000	1.000	1.000	0.847	0.924	0.380	1.000	0.594	1.000	1.000	1.000	0.446	1.000	0.912	1.000	1.000
2038	1.000	0.806	0.836	1.000	0.953	0.858	0.638	1.000	1.000	1.000	1.000	0.808	0.908	0.347	1.000	0.552	1.000	1.000	1.000	0.421	1.000	0.865	1.000	1.000
2039	1.000	0.799	0.802	1.000	0.950	0.826	0.613	1.000	1.000	1.000	1.000	0.771	0.893	0.316	1.000	0.511	1.000	1.000	1.000	0.396	1.000	0.820	1.000	1.000
2040	1.000	0.792	0.770	1.000	0.948	0.796	0.588	1.000	1.000	1.000	1.000	0.736	0.878	0.286	1.000	0.472	1.000	1.000	1.000	0.373	1.000	0.776	1.000	1.000
2041	1.000	0.785	0.737	1.000	0.946	0.766	0.564	1.000	1.000	1.000	1.000	0.702	0.863	0.257	1.000	0.434	1.000	1.000	0.975	0.350	1.000	0.733	1.000	1.000
2042	1.000	0.778	0.706	1.000	0.943	0.737	0.540	1.000	0.987	1.000	1.000	0.670	0.848	0.228	1.000	0.397	1.000	1.000	0.948	0.328	1.000	0.691	1.000	1.000
2043	1.000	0.771	0.674	1.000	0.941	0.709	0.517	1.000	0.955	1.000	1.000	0.638	0.833	0.201	1.000	0.361	1.000	1.000	0.920	0.307	1.000	0.650	1.000	1.000
2044	1.000	0.764	0.643	1.000	0.938	0.682	0.493	1.000	0.922	1.000	1.000	0.608	0.819	0.173	1.000	0.325	1.000	1.000	0.893	0.287	1.000	0.609	1.000	1.000
2045	1.000	0.756	0.612	1.000	0.935	0.655	0.471	1.000	0.890	1.000	1.000	0.579	0.805	0.147	1.000	0.291	1.000	1.000	0.867	0.267	1.000	0.570	1.000	1.000
2046	1.000	0.749	0.581	0.993	0.933	0.629	0.448	1.000	0.859	1.000	1.000	0.550	0.790	0.121	1.000	0.258	1.000	1.000	0.841	0.249	1.000	0.533	1.000	1.000
2047	1.000	0.742	0.551	0.976	0.930	0.603	0.426	1.000	0.828	1.000	1.000	0.523	0.776	0.097	1.000	0.227	1.000	1.000	0.815	0.230	1.000	0.496	1.000	1.000
2048	1.000	0.735	0.520	0.958	0.927	0.577	0.403	1.000	0.798	1.000	1.000	0.495	0.761	0.072	1.000	0.196	1.000	1.000	0.788	0.213	1.000	0.461	1.000	1.000
2049	1.000	0.728	0.490	0.940	0.924	0.552	0.381	1.000	0.768	1.000	1.000	0.469	0.746	0.048	1.000	0.166	1.000	1.000	0.762	0.195	1.000	0.426	0.989	1.000
2050	1.000	0.721	0.459	0.922	0.921	0.527	0.359	1.000	0.738	1.000	1.000	0.442	0.731	0.025	1.000	0.136	1.000	1.000	0.736	0.178	1.000	0.391	0.961	1.000

Figure C-2. Mining water availability in the hydrological referent.

The implied impacts of the water-availability constraints in the hydrological and macroeconomic referents on potential GDP and employment are noted in Figure C-3 and Figure C-4, respectively.

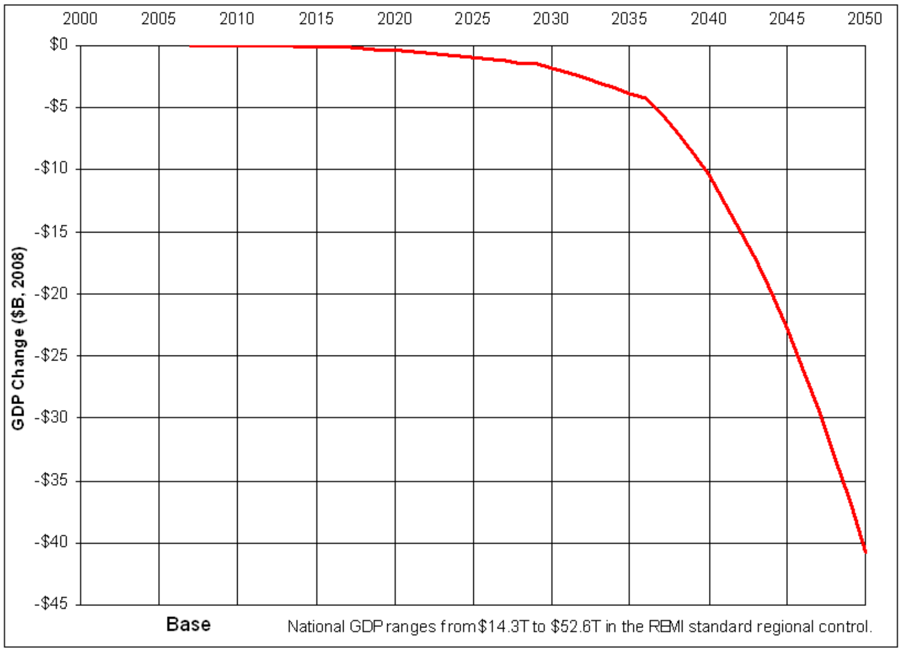

Figure C-3. National GDP impacts in the hydrological referent.

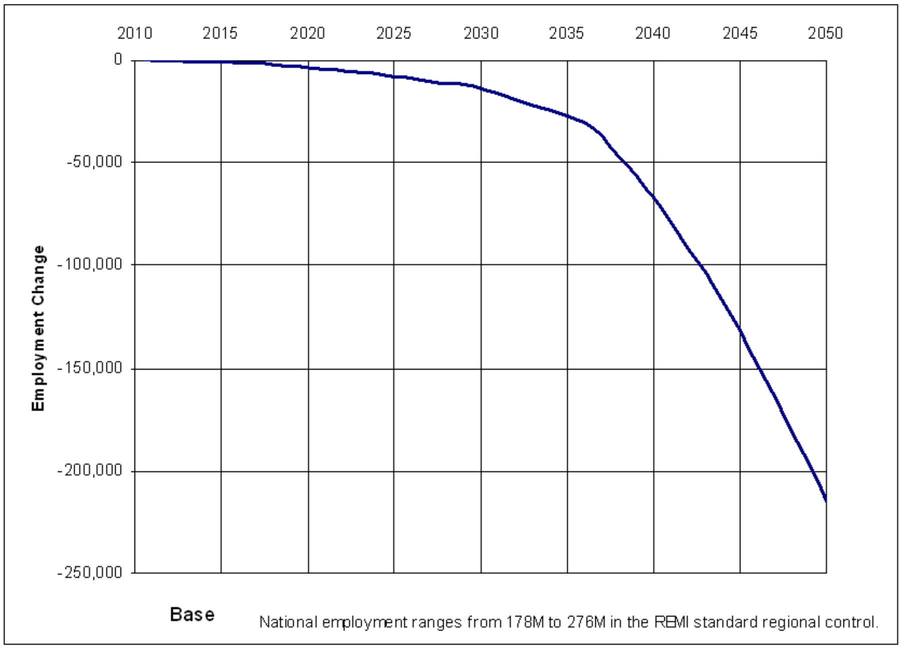

Figure C-4. National employment impacts in the hydrological referent.

Table C-1 provides a numerical listing of the implied impacts of water-availability constraints in the hydrological and macroeconomic referents. Note that the impacts are relatively small compared with the low-exceedance-probability climate impacts, such as in the $2 trillion in the 1% case. Nonetheless, the value of the implied impacts is nearly half the size of the 99% exceedance-probability results ($638 billion) in the body of the report, The national GDP loss due to predicted water constraints, even in the absence of climate change, is $316 billion (2008 $) at a 0% discount rate and $114 billion at a 3% discount rate. In other words, had the projected water shortages been included, the macroeconomic referent's forecast of the GDP (the starting point of the analysis) would have been $316 billion less at a 0% discount rate. Note again that none of these impacts are contained in the reported impacts of climate change. The climate-change impacts reflect only the difference between the referent and any simulation. See Section 3.2.4 for more information.

Table C-1. Base-Case Impacts

Base Case

Region	Change in GDP (0% D.R., $B)	Change in Empl. (1K Labor Yrs)	Change in Pop. (1K People)	Region	Change in GDP (0% D.R., $B)	Change in Empl. (1K Labor Yrs)	Change in Pop. (1K People)
United States	-$316.1	-1,873.6	0.0	Montana	-$0.6	-5.2	0.2
Alabama	-$1.5	-13.2	1.3	Nebraska	-$0.6	-3.8	1.0
Arizona	-$33.4	-207.5	-16.0	Nevada	-$24.4	-125.5	-8.1
Arkansas	-$0.7	-5.7	1.2	New Hampshire	-$0.5	-4.1	0.6
California	-$46.3	-251.3	8.3	New Jersey	-$5.7	-27.5	3.2
Colorado	-$2.5	-14.9	2.8	New Mexico	-$2.2	-17.2	-0.5
Connecticut	-$2.4	-11.2	1.4	New York	-$23.1	-78.4	6.5
Delaware	-$0.7	-3.7	0.2	North Carolina	-$5.3	-43.4	-1.1
District of Columbia	-$1.2	-4.6	0.2	North Dakota	-$0.4	-2.9	0.2
Florida	-$5.8	-40.1	9.4	Ohio	-$11.9	-75.9	-4.1
Georgia	-$3.9	-25.9	3.5	Oklahoma	-$1.3	-9.2	1.2
Idaho	-$0.5	-4.5	0.9	Oregon	-$0.9	-6.0	2.5
Illinois	-$5.0	-27.4	5.0	Pennsylvania	-$7.5	-56.9	0.2
Indiana	-$10.6	-64.3	-4.4	Rhode Island	-$0.4	-2.6	0.4
Iowa	-$1.1	-7.9	1.2	South Carolina	-$0.2	-14.9	-0.6
Kansas	-$0.9	-5.6	1.4	South Dakota	-$0.3	-2.2	0.4
Kentucky	-$3.8	-26.5	-1.2	Tennessee	-$19.7	-135.1	-7.6
Louisiana	-$2.4	-15.6	0.9	Texas	-$9.7	-55.4	11.2
Maine	-$0.4	-3.4	0.6	Utah	-$1.9	-14.1	1.0
Maryland	-$4.3	-26.0	0.8	Vermont	-$0.5	-4.0	0.1
Massachusetts	-$4.5	-23.7	2.6	Virginia	-$7.2	-50.0	-1.8
Michigan	-$6.2	-34.5	1.6	Washington	-$2.2	-11.0	3.7
Minnesota	-$1.9	-10.8	3.1	West Virginia	-$42.7	-258.4	-39.9
Mississippi	-$1.1	-8.6	0.5	Wisconsin	-$1.6	-10.5	2.7
Missouri	-$1.7	-11.2	2.9	Wyoming	-$1.1	-8.0	-0.5

Obs.: Changes in GDP and employment are summed over the 2010-2050 period; population is the 2050 value.

References

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Appendix D. National and State Reference Values

(REMI Base-Case Control Run)

The analysis results presented in the body of this report are based on comparing macroeconomic values in the base-case forecast of the REMI model, the macroeconomic referent, with simulation values. Thus, the analysis results are the differences between the estimated values without climate change and the simulated values with climate change. In this appendix, we simply report the macroeconomic values from the base-case forecast so that one can compare the impacts (changes) noted in the analysis results on national- and state-level GDP, employment, personal income, and population. Table D-1 summarizes the national values of these variables for three sample years from the base-case forecast. Although data for all years during the period of the study are available, we have selected three representative years as illustrative of the economic trend.

Table D-1. National Summary Values

REMI Summary - National			
	2007	2025	2050
National GDP ($B)	$14,396.5	$23,304.3	$52,577.0
Employment (1K People)	181,668.7	201,023.2	275,903.9
Personal Income ($B)	$14,285.9	$38,129.8	$185,936.6
Population (1K People)	301,697.4	356,252.5	431,634.3

Table D-2, Table D-3, and Table D-4 provide values for state-level contribution to the GDP, employment, and population, respectively, for the three sample years. As an example, from Table D-3, West Virginia is forecast to have 1.249 million people employed in 2050 in the macroeconomic referent that does not consider future climate change.

Table D-2. GDP Values (2008$) in Base Case

REMI Summary - GDP

Region	GDP ($B) 2007	GDP ($B) 2025	GDP ($B) 2050	Region	GDP ($B) 2007	GDP ($B) 2025	GDP ($B) 2050
United States	**$14,396.5**	**$23,304.3**	**$52,577.0**	Montana	$33.0	$49.2	$113.0
Alabama	$171.4	$250.6	$575.3	Nebraska	$75.1	$111.7	$246.5
Arizona	$267.5	$473.2	$1,284.1	Nevada	$133.5	$212.6	$497.2
Arkansas	$93.1	$137.6	$312.4	New Hampshire	$64.0	$113.0	$273.3
California	$1,946.8	$3,551.8	$9,567.8	New Jersey	$505.9	$843.0	$1,733.8
Colorado	$261.0	$434.6	$922.2	New Mexico	$67.0	$99.8	$220.0
Connecticut	$217.6	$383.0	$819.8	New York	$1,199.0	$2,337.3	$5,339.2
Delaware	$49.0	$77.1	$161.2	North Carolina	$375.7	$569.8	$1,237.7
District of Columbia	$105.9	$153.0	$266.9	North Dakota	$26.2	$38.9	$91.4
Florida	$807.2	$1,256.1	$2,752.7	Ohio	$491.1	$702.3	$1,473.6
Georgia	$430.6	$676.5	$1,437.7	Oklahoma	$131.7	$184.3	$358.6
Idaho	$52.6	$86.2	$217.3	Oregon	$162.5	$274.1	$679.1
Illinois	$671.8	$998.5	$1,896.7	Pennsylvania	$559.1	$849.3	$1,760.7
Indiana	$260.6	$377.4	$844.6	Rhode Island	$46.7	$75.3	$163.6
Iowa	$120.5	$179.7	$414.1	South Carolina	$162.6	$239.2	$534.5
Kansas	$119.2	$180.4	$399.4	South Dakota	$28.4	$42.5	$101.3
Kentucky	$155.0	$224.3	$497.5	Tennessee	$252.2	$383.2	$884.4
Louisiana	$166.2	$236.3	$505.0	Texas	$1,107.9	$1,716.0	$3,599.9
Maine	$48.0	$74.4	$177.5	Utah	$104.5	$172.6	$428.4
Maryland	$295.2	$449.5	$885.9	Vermont	$25.2	$42.0	$102.2
Massachusetts	$407.0	$739.2	$1,706.4	Virginia	$408.5	$609.3	$1,168.5
Michigan	$427.9	$611.4	$1,366.4	Washington	$325.7	$539.8	$1,249.5
Minnesota	$279.4	$446.0	$954.2	West Virginia	$56.7	$81.1	$174.9
Mississippi	$85.0	$124.3	$299.6	Wisconsin	$243.1	$352.5	$760.8
Missouri	$247.4	$365.5	$764.9	Wyoming	$24.5	$33.4	$66.0

Table D-3. Employment Values in Base Case

REMI Summary - Employment

Region	Employment (1K People)			Region	Employment (1K People)		
	2007	2025	2050		2007	2025	2050
United States	**181,668.7**	**201,023.2**	**275,903.9**	Montana	648.2	691.3	946.3
Alabama	2,629.7	2,667.1	3,633.6	Nebraska	1,260.0	1,293.1	1,688.0
Arizona	3,427.1	4,277.7	7,142.0	Nevada	1,653.3	1,995.6	3,041.7
Arkansas	1,629.6	1,656.0	2,206.3	New Hampshire	872.4	1,032.7	1,518.1
California	20,858.1	25,805.3	42,573.6	New Jersey	5,250.7	6,044.3	7,817.8
Colorado	3,241.5	3,797.3	5,001.3	New Mexico	1,118.7	1,199.4	1,639.6
Connecticut	2,291.6	2,716.3	3,598.3	New York	11,279.2	14,183.8	19,805.2
Delaware	554.0	620.3	817.5	North Carolina	5,401.3	5,723.9	7,632.1
District of Columbia	819.5	897.2	1,095.0	North Dakota	492.6	506.1	691.2
Florida	10,781.8	12,110.2	16,457.8	Ohio	6,991.9	6,940.1	8,721.5
Georgia	5,499.9	6,081.5	7,886.2	Oklahoma	2,184.1	2,164.7	2,550.3
Idaho	919.1	1,035.8	1,554.2	Oregon	2,327.4	2,681.6	4,031.8
Illinois	7,744.8	8,043.8	9,579.3	Pennsylvania	7,430.0	7,971.3	10,368.3
Indiana	3,785.0	3,706.4	4,816.5	Rhode Island	631.3	706.8	962.1
Iowa	2,053.0	2,072.1	2,757.7	South Carolina	2,484.8	2,590.7	3,446.4
Kansas	1,876.0	1,911.6	2,424.0	South Dakota	564.3	577.7	792.8
Kentucky	2,462.9	2,427.0	3,131.0	Tennessee	3,795.7	3,995.6	5,442.4
Louisiana	2,510.1	2,505.0	3,224.4	Texas	13,795.8	15,031.5	19,580.4
Maine	857.1	932.0	1,324.4	Utah	1,626.4	1,877.9	2,807.3
Maryland	3,460.6	3,808.8	4,834.7	Vermont	437.9	498.9	732.3
Massachusetts	4,299.5	5,276.1	7,712.2	Virginia	4,929.5	5,246.5	6,390.4
Michigan	5,596.7	5,500.6	7,221.2	Washington	3,947.0	4,469.7	5,985.1
Minnesota	3,620.7	3,956.9	5,269.7	West Virginia	941.2	952.4	1,249.6
Mississippi	1,555.6	1,561.5	2,135.7	Wisconsin	3,658.2	3,640.9	4,615.5
Missouri	3,739.4	3,830.2	4,798.1	Wyoming	384.5	387.3	482.2

Table D-4. Population Values in Base Case

REMI Summary - Population

Region	Population (1K People)			Region	Population (1K People)		
	2007	2025	2050		2007	2025	2050
United States	**301,697.4**	**356,252.5**	**431,634.3**	Montana	960.7	1,157.0	1,370.1
Alabama	4,655.9	5,376.4	6,505.1	Nebraska	1,777.1	1,981.7	2,341.0
Arizona	6,333.5	9,072.9	13,178.3	Nevada	2,595.4	3,957.9	5,565.1
Arkansas	2,834.0	3,165.3	3,764.4	New Hampshire	1,323.3	1,622.9	2,045.4
California	36,461.9	44,179.3	60,212.1	New Jersey	8,707.4	10,249.0	12,081.6
Colorado	4,845.4	6,254.8	7,673.4	New Mexico	1,968.9	2,352.0	2,786.1
Connecticut	3,505.1	4,151.4	4,867.2	New York	19,320.2	23,622.1	28,435.4
Delaware	867.6	1,087.9	1,304.0	North Carolina	9,026.8	11,067.5	13,746.4
District of Columbia	586.0	687.6	760.6	North Dakota	640.4	717.9	858.0
Florida	18,435.3	23,667.8	29,182.5	Ohio	11,471.8	11,721.0	12,811.1
Georgia	9,564.5	12,310.0	15,097.4	Oklahoma	3,627.4	4,179.0	4,411.2
Idaho	1,496.5	1,927.7	2,486.3	Oregon	3,732.4	4,556.1	5,809.2
Illinois	12,832.5	13,865.1	15,120.9	Pennsylvania	12,428.5	13,796.8	15,955.4
Indiana	6,348.2	6,697.8	7,634.3	Rhode Island	1,056.7	1,162.6	1,420.4
Iowa	2,982.7	3,189.2	3,772.4	South Carolina	4,401.5	5,243.1	6,296.5
Kansas	2,776.8	3,102.9	3,568.2	South Dakota	796.4	902.1	1,095.7
Kentucky	4,233.5	4,589.4	5,264.9	Tennessee	6,180.9	7,382.6	9,152.0
Louisiana	4,239.9	4,320.0	4,670.8	Texas	23,934.4	30,166.7	35,335.9
Maine	1,318.9	1,497.3	1,859.6	Utah	2,638.1	3,438.7	4,519.9
Maryland	5,627.7	6,422.6	7,321.0	Vermont	621.7	721.2	908.2
Massachusetts	6,443.3	7,636.5	9,593.5	Virginia	7,669.6	8,806.8	9,941.3
Michigan	10,081.8	10,003.8	11,250.9	Washington	6,438.9	7,706.5	9,256.7
Minnesota	5,179.7	5,872.0	6,931.8	West Virginia	1,815.9	1,988.8	2,270.4
Mississippi	2,928.2	3,259.5	3,853.8	Wisconsin	5,599.6	5,942.5	6,717.4
Missouri	5,892.3	6,571.2	7,363.0	Wyoming	521.9	627.4	696.2

Table D-5 lists the sums of GDP and employment from 2010 to 2050 for comparison with summary-risk values presented in the body of the report. Note that the population column in Table D-5 reflects only the number of people in 2050 and thus does not contain summed values. As an example from Table D-5, from 2010 to 2050 West Virginia is forecast to produce a GDP of $4,139 billion with approximately 42,000 labor years of work. In 2050, the population of West Virginia is estimated to be 2,270,400. Note that the values in all tables in this appendix are raw numbers; no discount rate has been applied to any monetary quantity.

Table D-5. REMI Control Totals from 2010 to 2050 for Comparison with Summary-Risk Values

REMI Control

Region	Actual GDP (0% D.R., $B)	Total Empl. (1K Labor Yrs)	Total Pop. (1K People)	Region	Actual GDP (0% D.R., $B)	Total Empl. (1K Labor Yrs)	Total Pop. (1K People)
United States	$1,205,010.9	8,904,915.3	431,634.3	Montana	2,539.9	30,394.7	1,370.1
Alabama	13,060.5	118,619.9	6,505.1	Nebraska	$5,729.1	56,687.1	2,341.0
Arizona	26,227.5	200,555.2	13,178.3	Nevada	$11,162.4	91,094.1	5,565.1
Arkansas	7,135.0	73,129.3	3,764.4	New Hampshire	$5,966.5	46,500.4	2,045.4
California	194,884.5	1,198,924.8	60,212.1	New Jersey	$42,181.7	263,489.3	12,081.6
Colorado	21,930.5	165,784.1	7,673.4	New Mexico	$5,092.0	53,022.3	2,786.1
Connecticut	19,398.5	118,904.9	4,867.2	New York	$121,460.4	629,356.1	28,435.4
Delaware	3,886.2	27,241.3	1,304.0	North Carolina	$29,140.7	252,978.9	13,746.4
District of Columbia	7,272.2	38,755.3	760.6	North Dakota	$2,030.8	22,345.7	858.0
Florida	64,499.4	536,695.5	29,182.5	Ohio	$35,371.5	301,487.9	12,811.1
Georgia	34,271.8	265,741.3	15,097.4	Oklahoma	$8,950.0	91,851.1	4,411.2
Idaho	4,611.7	46,843.1	2,486.3	Oregon	$14,566.7	121,380.6	5,809.2
Illinois	48,640.4	344,045.3	15,120.9	Pennsylvania	$42,663.9	349,127.0	15,955.4
Indiana	19,473.5	162,758.6	7,634.3	Rhode Island	$3,838.8	31,282.5	1,420.4
Iowa	9,381.4	91,479.9	3,772.4	South Carolina	$12,348.1	114,323.0	6,296.5
Kansas	9,252.4	83,063.4	3,568.2	South Dakota	$2,236.8	25,611.3	1,095.7
Kentucky	11,542.1	106,435.9	5,264.9	Tennessee	$20,007.5	177,343.7	9,152.0
Louisiana	11,936.5	109,264.6	4,670.8	Texas	$85,902.3	654,617.7	35,335.9
Maine	3,926.9	41,776.4	1,859.6	Utah	$9,189.2	84,752.5	4,519.9
Maryland	22,244.7	165,901.4	7,321.0	Vermont	$2,228.0	22,514.4	908.2
Massachusetts	38,408.6	237,246.6	9,593.5	Virginia	$29,819.8	225,968.7	9,941.3
Michigan	31,493.7	241,971.3	11,250.9	Washington	$28,088.4	196,111.5	9,256.7
Minnesota	22,553.5	173,726.5	6,931.8	West Virginia	$4,139.0	41,932.1	2,270.4
Mississippi	6,587.4	69,447.8	3,853.8	Wisconsin	$17,941.5	158,508.4	6,717.4
Missouri	18,401.9	166,139.1	7,363.0	Wyoming	$1,632.1	16,624.6	696.2

Obs.: GDP and employment are summed over the 2010-2050 period; population is the 2050 value.

Appendix E. 1% Exceedance-Probability Impacts

National and State

This appendix provides detailed national and state information at the 1% exceedance probability. Our interest in this study has been to address the full range of possibilities of climate change, including the impacts of events that have a low probability and also a high consequence. The analysis results at the 1% exceedance probability in this appendix represent the worst-case example in our study and provide a more in-depth look at the impacts and their volatility by state and industry over time. The analysis results are the differences between the values forecast without climate change (from the macroeconomic referent discussed in Appendices C and D) and the simulated values with climate change. Note that the analysis results are based on a single motif as discussed in the main text. Thus, the results presented for any particular year are realizable for that time period but should not be considered a point prediction (see the discussion of motif in Section 3.1).

Note that some states experience a change in the sign of the impacts (from positive to negative or vice versa) or a reversal in the magnitude of the impacts. For example, a state may initially be positively affected because it has adequate water, but reduced precipitation in later years finally has an overall negative impact on the state. Conversely, a state may initially be negatively affected because of reduced precipitation, but the state may be positively affected (e.g., losses are reduced) in later years because the states surrounding it suffer more.

Table E-1 shows the GDP impacts for industry at the national level by decade. The values in this table and other “by decade” tables in this appendix are not cumulative over the particular decades. Thus, the values listed in Table E-1 for, say, 2050, for all industries listed represent only the GDP impacts for 2050, not a summation of such impacts from 2040 to 2050. Taking the ambulatory health care services industry as an example, we note that in 2050 this industry is estimated to experience a loss of $11.3 billion at the 1% exceedance probability. This loss is due to reduced labor earnings reducing the demand for health care along with the demand for other goods and services.

Table E-2 provides the contribution of individual states to the GDP by decade at the 1% exceedance probability. The entry for the United States (entire nation) in the table includes the impacts on Alaska and Hawaii, which are not listed in the table. Each succeeding decadal value for the United States (on the first row) is reflective of the overall downward trend. Most states at these 10-year marks are also illustrative of this trend, though there is some volatility in loss in a few of the states, like California, and no loss in some states such as Idaho, Oregon, and Washington.

Table E-3 and Table E-4 illustrate the yearly changes in the contributions to the GDP by individual states. These tables highlight the volatility as well as the potential change in the sign of impacts for some states. Taking New Mexico as an example, we observe the volatility at the 1% exceedance probability beginning in 2012, where the loss goes back and forth from $0.2 to $0.1 billion until 2015 when the loss jumps by a factor of 10 to

$1.2 billion. Similar volatility is present to 2050, reflective of the overall downward trend in the state's contribution to the GDP. In 2050, the impact reaches $2.9 billion, which is the greatest loss for New Mexico in the whole 40-year period.

Table E-5 shows the employment impacts per state by decade. As an example, the impact of climate change on West Virginia is a loss of 54,200 jobs in 2050 at the 1% exceedance probability. To determine the difference between this value and the employment value estimated in the base-case referent (in Appendix D, Table D-2), we subtract 54,200 from 1,249,000. This difference, 1,194,800, reflects the adjustment to the base case for 2050 as a result of climate change. In effect, the employment in West Virginia grows, but it grows more slowly with climate change.

Finally, Table E-6 through Table E-24 display the impacts for each state by industry-group with decadal resolution at the 1% exceedance probability. The values listed in each of these tables represent a particular industry's contribution (i.e., value-added output) to the GDP. To explain the contents of this data set, we look at Table E-10, which gives the contribution to the GDP by the educational services industry in 2020, 2030, 2040, and 2050. In 2050, Connecticut, Colorado, New Mexico, West Virginia, and Wisconsin all show a loss of $4.9 million as a result of climate change at the 1% exceedance probability. On the other hand, the educational services industry in 2050 does show positive impacts for some states. For example, from a loss in 2040 of $6.1 billion, this industry shows a gain of $11 million in 2050 in this worst-case example. Part of the explanation could be that people from other states that suffer as a result of climate change will have moved to California and led to growth in the educational services industry.

Table E-1. Change in GDP Contribution by Industry (1% Case)

Change in Contribution to GDP ($B) - 1% Case

Category	2010	2020	2030	2040	2050
Forestry and logging; Fishing, hunting, and trapping	-$0.001	-$0.016	-$0.023	-$0.017	-$0.005
Agriculture and forestry support activities; Other	$0.000	-$0.005	-$0.009	-$0.013	-$0.021
Oil and gas extraction	$0.028	-$0.021	-$1.578	-$0.393	-$0.968
Mining (except oil and gas)	$0.000	-$0.060	-$3.233	-$10.390	-$17.324
Support activities for mining	$0.000	-$0.047	-$0.295	-$0.703	-$1.483
Utilities	$0.425	$0.129	$0.873	$1.557	$0.274
Construction	-$0.023	-$0.695	-$1.583	-$1.658	-$2.197
Wood product manufacturing	$0.000	-$0.022	-$0.061	-$0.073	-$0.077
Nonmetallic mineral product manufacturing	$0.001	-$0.038	-$0.142	-$0.251	-$0.430
Primary metal manufacturing	$0.007	-$0.021	-$0.109	-$0.256	-$0.455
Fabricated metal product manufacturing	$0.007	-$0.070	-$0.197	-$0.267	-$0.297
Machinery manufacturing	$0.083	-$0.033	-$0.169	-$0.894	-$2.126
Computer and electronic product manufacturing	$0.001	-$0.094	-$0.371	-$0.765	-$1.640
Electrical equipment and appliance manufacturing	$0.038	-$0.010	$0.029	$0.028	$0.029
Motor vehicles, bodies & trailers, and parts manufacturing	$0.001	-$0.071	-$0.338	-$0.748	-$1.334
Other transportation equipment manufacturing	$0.000	-$0.004	-$0.054	-$0.138	-$0.262
Furniture and related product manufacturing	$0.000	-$0.032	-$0.125	-$0.273	-$0.555
Miscellaneous manufacturing	$0.000	$0.029	$0.022	$0.092	$0.289
Food manufacturing	-$0.045	-$0.847	-$2.020	-$4.001	-$7.082
Beverage and tobacco product manufacturing	-$0.022	-$0.371	-$0.817	-$1.438	-$2.184
Textile mills	$0.000	$0.001	$0.000	$0.001	$0.001
Textile product mills	$0.000	-$0.005	-$0.027	-$0.075	-$0.200
Apparel manufacturing	$0.000	$0.017	$0.028	$0.055	$0.111
Leather and allied product manufacturing	-$0.001	-$0.026	-$0.064	-$0.109	-$0.142
Paper manufacturing	-$0.001	-$0.038	-$0.114	-$0.196	-$0.321
Printing and related support activities	$0.000	-$0.012	-$0.033	-$0.042	-$0.043
Petroleum and coal product manufacturing	$0.002	-$0.015	-$0.149	-$0.370	-$0.650
Chemical manufacturing	-$0.001	-$0.154	-$0.662	-$1.509	-$2.981
Plastics and rubber product manufacturing	$0.000	-$0.065	-$0.212	-$0.340	-$0.437
Wholesale trade	-$0.015	-$0.703	-$1.891	-$3.035	-$4.424
Retail trade	-$0.071	-$1.223	-$3.875	-$8.746	-$17.328
Air transportation	$0.000	-$0.053	-$0.190	-$0.324	-$0.437
Rail transportation	$0.004	-$0.021	-$0.116	-$0.310	-$0.535

Category	2010	2020	2030	2040	2050
Water transportation	$0.000	$0.001	$0.000	$0.000	$0.000
Truck transportation; Couriers and messengers	-$0.001	-$0.195	-$0.764	-$1.610	-$2.647
Transit and ground passenger transportation	$0.001	-$0.004	-$0.029	-$0.056	-$0.084
Pipeline transportation	$0.007	-$0.001	-$0.011	-$0.018	-$0.036
Scenic and sightseeing transportation; support activities	$0.000	-$0.010	-$0.036	-$0.061	-$0.080
Warehousing and storage	$0.000	-$0.033	-$0.102	-$0.159	-$0.189
Publishing industries, except Internet	$0.000	-$0.136	-$0.466	-$0.950	-$1.820
Motion picture and sound recording industries	$0.000	-$0.036	-$0.138	-$0.343	-$0.763
Internet publishing and broadcasting; ISPs, search portals, and data processing; Other information services	$0.001	-$0.114	-$0.448	-$0.864	-$1.397
Broadcasting, except Internet; Telecommunications	$0.004	-$0.263	-$1.094	-$2.251	-$3.979
Monetary authorities - central bank; Credit intermediation and related activities; Funds, trusts, & other financial vehicles	$0.005	-$0.402	-$1.448	-$2.644	-$4.150
Securities, commodity contracts, investments	$0.002	-$0.426	-$1.737	-$3.348	-$5.065
Insurance carriers and related activities	$0.006	-$0.058	-$0.311	-$0.569	-$0.852
Real estate	$0.013	-$0.433	-$1.806	-$3.313	-$5.374
Rental and leasing services; Lessors of nonfinancial intangible assets	$0.006	-$0.100	-$0.700	-$0.579	-$0.671
Professional and technical services	$0.018	-$0.580	-$2.064	-$3.193	-$4.421
Management of companies and enterprises	-$0.005	-$0.233	-$0.742	-$1.036	-$1.053
Administrative and support services	$0.007	-$0.240	-$0.962	-$1.689	-$2.594
Waste management and remediation services	$0.001	-$0.010	-$0.042	-$0.045	-$0.044
Educational services	$0.001	-$0.016	-$0.095	-$0.200	-$0.343
Ambulatory health care services	$0.001	-$0.484	-$2.205	-$5.377	-$11.334
Hospitals	$0.005	-$0.027	-$0.208	-$0.491	-$0.993
Nursing and residential care facilities	$0.000	-$0.013	-$0.071	-$0.158	-$0.329
Social assistance	$0.001	-$0.009	-$0.067	-$0.166	-$0.371
Performing arts and spectator sports	$0.000	-$0.027	-$0.088	-$0.153	-$0.219
Museums, historical sites, zoos, and parks	$0.000	-$0.001	-$0.006	-$0.015	-$0.029
Amusement, gambling, and recreation	-$0.001	-$0.044	-$0.212	-$0.528	-$0.988
Accommodation	-$0.002	-$0.049	-$0.154	-$0.286	-$0.436
Food services and drinking places	-$0.040	-$0.338	-$0.649	-$1.022	-$1.323
Repair and maintenance	$0.001	-$0.053	-$0.209	-$0.394	-$0.633
Personal and laundry services	-$0.001	-$0.094	-$0.377	-$0.864	-$1.729
Membership associations and organizations	$0.001	-$0.016	-$0.081	-$0.163	-$0.284
Private households	$0.000	-$0.012	-$0.044	-$0.078	-$0.122

Table E-2. Change in GDP Contribution by State (1% Case)

Change in GDP ($B) - 1% Case

Region	2010	2020	2030	2040	2050	Region	2010	2020	2030	2040	2050
United States	**$0.5**	**-$10.2**	**-$38.4**	**-$74.3**	**-$130.0**	Montana	$0.0	$0.0	$0.0	-$0.1	-$0.1
Alabama	$0.0	-$0.2	-$0.6	-$0.9	-$2.2	Nebraska	$0.0	$0.0	-$0.1	-$0.3	-$0.6
Arizona	$0.2	-$0.5	-$2.5	-$5.2	-$5.8	Nevada	$0.0	-$0.1	-$1.0	-$3.6	-$2.4
Arkansas	$0.0	-$0.1	-$0.3	-$0.5	-$1.2	New Hampshire	$0.0	$0.0	$0.0	-$0.1	-$0.2
California	$0.3	-$0.4	-$2.2	-$5.1	-$2.5	New Jersey	$0.0	-$0.3	-$1.0	-$1.6	-$2.9
Colorado	$0.0	-$0.1	-$1.6	-$1.5	-$2.4	New Mexico	$0.0	-$0.2	-$1.6	-$1.7	-$2.4
Connecticut	$0.0	-$0.1	-$0.3	-$0.5	-$0.9	New York	-$0.1	-$1.0	-$3.1	-$6.0	-$10.4
Delaware	$0.0	$0.0	-$0.1	-$0.2	-$0.3	North Carolina	$0.0	-$0.6	-$1.2	-$2.2	-$4.2
D.C.	$0.0	$0.0	-$0.1	-$0.3	-$0.5	North Dakota	$0.0	$0.0	$0.0	-$0.1	-$0.2
Florida	-$0.1	-$1.6	-$3.0	-$4.8	-$7.8	Ohio	$0.0	$0.0	-$1.1	-$2.9	-$5.8
Georgia	$0.0	-$1.0	-$2.0	-$3.3	-$6.2	Oklahoma	$0.0	-$0.4	-$2.9	-$1.5	-$3.6
Idaho	$0.0	$0.0	$0.0	$0.1	$0.1	Oregon	$0.0	$0.2	$0.2	$0.6	$1.1
Illinois	$0.0	$0.1	$0.0	-$1.3	-$5.2	Pennsylvania	$0.0	-$0.6	-$1.4	-$2.5	-$4.8
Indiana	$0.0	$0.0	-$0.5	-$2.0	-$4.7	Rhode Island	$0.0	$0.0	$0.0	$0.0	-$0.1
Iowa	$0.0	$0.0	$0.0	-$0.4	-$1.1	South Carolina	$0.0	-$0.2	-$0.5	-$0.8	-$1.6
Kansas	$0.0	-$0.1	-$0.3	-$0.4	-$1.0	South Dakota	$0.0	$0.0	$0.0	-$0.1	-$0.2
Kentucky	$0.0	-$0.2	-$0.5	-$2.9	-$6.8	Tennessee	$0.0	-$0.4	-$1.2	-$2.9	-$5.3
Louisiana	$0.0	-$0.1	-$0.4	-$0.6	-$1.3	Texas	$0.0	-$1.3	-$3.6	-$5.4	-$9.8
Maine	$0.0	$0.0	$0.0	$0.0	-$0.1	Utah	$0.0	-$0.1	-$0.6	-$1.7	-$1.8
Maryland	$0.0	-$0.2	-$0.6	-$1.0	-$1.9	Vermont	$0.0	$0.0	$0.0	-$0.1	-$0.2
Massachusetts	$0.0	$0.0	-$0.3	-$0.5	-$1.1	Virginia	$0.0	-$0.4	-$1.1	-$1.9	-$3.6
Michigan	$0.0	-$0.1	-$0.3	-$1.5	-$3.3	Washington	$0.0	$0.2	$0.2	$0.8	$1.3
Minnesota	$0.0	$0.0	-$0.1	-$0.7	-$2.0	West Virginia	$0.0	-$0.1	-$2.1	-$5.0	-$9.3
Mississippi	$0.0	$0.0	-$0.1	-$0.3	-$0.7	Wisconsin	$0.0	$0.0	-$0.1	-$0.6	-$1.8
Missouri	$0.0	$0.0	-$0.1	-$0.5	-$1.7	Wyoming	$0.0	$0.0	-$0.2	-$0.3	-$0.9

Table E-3. Change in GDP Contribution by State and Year (in Billions)

Change in GDP - 1% Case (Alabama to Montana)

Year	AL	AZ	AR	CA	CO	CT	DE	DC	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT
2010	$0.0	$0.2	$0.0	$0.3	$0.0	$0.0	$0.0	$0.0	-$0.1	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0
2011	-$0.1	$0.0	$0.0	$0.5	$0.0	$0.0	$0.0	$0.0	-$0.3	-$0.2	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	-$0.1	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0
2012	-$0.1	-$0.2	$0.0	$0.0	-$0.1	-$0.1	$0.0	$0.0	-$0.6	-$0.3	$0.0	$0.0	$0.0	$0.0	$0.0	-$0.1	-$0.1	$0.0	-$0.1	-$0.1	-$0.1	$0.0	$0.0	$0.0	$0.0
2013	-$0.1	-$0.1	$0.0	$0.3	$0.0	-$0.1	$0.0	$0.0	-$0.7	-$0.4	$0.0	$0.0	$0.0	$0.0	$0.0	-$0.1	-$0.1	$0.0	-$0.1	-$0.1	-$0.1	$0.0	$0.0	$0.0	$0.0
2014	-$0.2	-$0.2	-$0.1	$0.0	-$0.1	-$0.1	$0.0	$0.0	-$1.0	-$0.6	$0.0	$0.0	-$0.1	$0.1	-$0.1	-$0.1	-$0.1	$0.0	-$0.2	-$0.1	-$0.1	$0.0	$0.0	$0.0	$0.0
2015	-$0.2	-$1.3	-$0.1	-$1.2	-$2.3	-$0.2	-$0.1	-$0.1	-$1.6	-$0.7	-$0.1	-$0.1	-$0.1	$0.0	-$0.4	-$0.2	-$0.3	$0.0	-$0.3	-$0.3	-$0.2	-$0.2	-$0.1	-$0.2	$0.0
2016	-$0.3	-$1.7	-$0.1	-$1.0	-$0.4	-$0.1	-$0.1	$0.0	-$1.5	-$0.8	$0.0	-$0.2	-$0.1	$0.0	-$0.1	-$0.2	-$0.2	$0.0	-$0.2	-$0.2	-$0.2	-$0.1	-$0.1	-$0.1	$0.0
2017	-$0.2	-$1.0	-$0.1	-$0.4	-$0.2	-$0.1	$0.0	$0.0	-$1.5	-$0.9	$0.0	$0.0	-$0.1	$0.0	-$0.1	-$0.2	-$0.2	$0.0	-$0.2	-$0.1	-$0.1	$0.0	-$0.1	$0.0	$0.0
2018	-$0.3	-$1.8	-$0.2	-$0.8	-$1.2	-$0.2	-$0.1	-$0.1	-$1.9	-$1.1	$0.0	-$0.3	-$0.2	$0.0	-$0.4	-$0.3	-$0.3	$0.0	-$0.3	-$0.3	-$0.3	-$0.2	-$0.1	-$0.2	$0.0
2019	-$0.2	-$0.6	-$0.1	-$0.8	-$0.2	-$0.1	$0.0	$0.0	-$1.6	-$1.1	$0.0	$0.0	$0.0	$0.0	-$0.1	-$0.2	-$0.2	$0.0	-$0.2	-$0.1	-$0.1	$0.0	-$0.1	$0.0	$0.0
2020	-$0.2	-$0.5	-$0.1	-$0.4	-$0.1	-$0.1	$0.0	$0.0	-$1.6	-$1.0	$0.0	$0.1	$0.0	$0.0	-$0.1	-$0.2	-$0.1	$0.0	-$0.2	$0.0	-$0.1	$0.0	$0.0	$0.0	$0.0
2021	-$0.3	-$2.0	-$0.1	-$1.2	-$0.8	-$0.1	-$0.1	-$0.1	-$1.9	-$1.1	$0.0	$0.0	-$0.1	$0.0	-$0.1	-$0.2	-$0.2	$0.0	-$0.3	-$0.2	-$0.2	-$0.1	-$0.1	-$0.1	$0.0
2022	-$0.3	-$1.2	-$0.1	-$0.3	-$0.5	-$0.1	-$0.1	-$0.1	-$1.8	-$1.1	$0.0	$0.1	$0.0	$0.0	-$0.1	-$0.2	-$0.2	$0.0	-$0.2	-$0.1	-$0.1	$0.0	-$0.1	$0.0	$0.0
2023	-$0.3	-$2.2	-$0.1	-$1.0	-$0.2	-$0.1	-$0.1	-$0.1	-$1.8	-$1.1	$0.0	$0.2	-$0.1	$0.0	-$0.1	-$0.2	-$0.2	$0.0	-$0.3	-$0.1	$0.0	$0.0	-$0.1	$0.0	$0.0
2024	-$0.3	-$1.1	-$0.1	-$0.5	-$0.1	-$0.1	-$0.1	$0.0	-$1.7	-$1.1	$0.0	$0.2	$0.0	$0.0	-$0.1	-$0.2	-$0.1	$0.0	-$0.2	$0.0	-$0.1	$0.0	$0.0	$0.1	$0.0
2025	-$0.3	-$1.8	-$0.1	-$1.0	-$0.1	-$0.1	-$0.1	-$0.1	-$2.0	-$1.2	$0.0	$0.2	-$0.1	$0.0	-$0.1	-$0.2	-$0.1	$0.0	-$0.3	-$0.1	-$0.1	$0.0	$0.0	$0.1	$0.0
2026	-$0.3	-$2.4	-$0.1	-$1.2	-$0.2	-$0.1	-$0.1	-$0.1	-$2.1	-$1.3	$0.0	$0.2	-$0.1	$0.0	-$0.1	-$0.2	-$0.2	$0.0	-$0.3	-$0.1	-$0.1	$0.0	-$0.1	$0.0	$0.0
2027	-$0.2	-$2.1	-$0.1	-$2.2	-$0.2	-$0.2	-$0.1	-$0.1	-$2.2	-$1.3	$0.0	$0.1	-$0.1	$0.0	-$0.1	-$0.3	-$0.2	$0.0	-$0.4	-$0.2	-$0.2	-$0.1	-$0.1	$0.0	$0.0
2028	-$0.3	-$1.9	-$0.2	-$2.0	-$0.2	-$0.2	-$0.1	-$0.1	-$2.7	-$1.6	$0.0	$0.0	-$0.2	$0.0	-$0.2	-$0.4	-$0.2	$0.0	-$0.5	-$0.2	-$0.3	-$0.1	-$0.1	-$0.1	$0.0
2029	-$0.6	-$2.9	-$0.3	-$3.8	-$2.4	-$0.4	-$0.1	-$0.2	-$3.2	-$2.0	$0.0	-$0.3	-$0.4	-$0.1	-$0.5	-$1.2	-$0.5	$0.0	-$0.7	-$0.5	-$0.5	-$0.3	-$0.2	-$0.3	-$0.1
2030	-$0.6	-$2.5	-$0.3	-$2.2	-$1.6	-$0.3	-$0.1	-$0.1	-$3.0	-$2.0	$0.0	$0.0	-$0.5	$0.0	-$0.3	-$0.5	-$0.4	$0.0	-$0.6	-$0.3	-$0.3	-$0.1	-$0.1	-$0.1	$0.0
2031	-$0.4	-$2.0	-$0.2	-$1.9	-$0.8	-$0.2	-$0.1	-$0.1	-$2.9	-$1.8	$0.0	$0.1	-$0.2	$0.0	-$0.3	-$0.5	-$0.3	$0.0	-$0.5	-$0.2	-$0.2	-$0.3	-$0.1	-$0.1	$0.0
2032	-$0.6	-$1.8	-$0.2	-$1.2	-$0.3	-$0.2	-$0.1	-$0.1	-$3.0	-$2.1	$0.0	-$0.2	-$0.8	-$0.1	-$0.2	-$0.6	-$0.3	$0.0	-$0.6	-$0.2	-$0.4	-$0.3	-$0.1	$0.0	$0.0
2033	-$0.5	-$2.0	-$0.3	-$1.4	-$0.8	-$0.3	-$0.1	-$0.1	-$3.3	-$2.2	$0.0	-$0.3	-$0.9	-$0.1	-$0.4	-$0.7	-$0.4	$0.0	-$0.6	-$0.3	-$0.4	-$0.2	-$0.2	-$0.1	$0.0
2034	-$0.6	-$2.3	-$0.3	-$1.3	-$0.5	-$0.2	-$0.1	-$0.1	-$3.3	-$2.3	$0.0	-$0.2	-$0.5	-$0.1	-$0.2	-$0.6	-$0.3	$0.0	-$0.5	-$0.2	-$0.7	-$0.3	-$0.2	-$0.1	$0.0
2035	-$0.8	-$3.2	-$0.5	-$2.9	-$1.3	-$0.4	-$0.2	-$0.2	-$4.3	-$2.9	$0.0	-$1.5	-$1.6	-$0.3	-$0.6	-$2.1	-$0.6	$0.0	-$0.8	-$0.5	-$1.1	-$0.5	-$0.3	-$0.7	-$0.1
2036	-$0.9	-$3.7	-$0.5	-$3.9	-$2.1	-$0.5	-$0.2	-$0.2	-$4.2	-$3.0	$0.0	-$2.0	-$1.9	-$0.5	-$0.7	-$2.5	-$0.6	$0.0	-$0.9	-$0.6	-$1.0	-$0.8	-$0.3	-$0.6	-$0.1
2037	-$0.8	-$4.2	-$0.4	-$3.8	-$0.8	-$0.2	-$0.1	-$0.1	-$3.8	-$2.7	$0.0	-$0.5	-$0.6	-$0.3	-$0.3	-$0.8	-$0.4	$0.0	-$0.5	-$0.2	-$1.0	-$0.8	-$0.2	-$0.3	$0.0
2038	-$0.7	-$3.8	-$0.4	-$2.9	-$0.3	-$0.3	-$0.1	-$0.2	-$3.8	-$2.7	$0.1	-$0.6	-$1.0	-$0.3	-$0.3	-$1.5	-$0.4	$0.0	-$0.7	-$0.2	-$0.7	-$1.0	-$0.2	-$0.3	$0.0
2039	-$0.8	-$1.9	-$0.4	-$2.8	-$0.1	-$0.3	-$0.2	-$0.2	-$4.0	-$2.9	$0.1	-$0.9	-$1.7	-$0.3	-$0.3	-$2.3	-$0.4	$0.0	-$0.8	-$0.2	-$0.9	-$0.7	-$0.2	-$0.3	$0.0
2040	-$0.9	-$5.2	-$0.5	-$5.1	-$1.5	-$0.5	-$0.2	-$0.3	-$4.8	-$3.3	$0.1	-$1.3	-$2.0	-$0.4	-$0.4	-$2.9	-$0.6	$0.0	-$1.0	-$0.5	-$1.5	-$0.7	-$0.3	-$0.5	-$0.1
2041	-$1.1	-$4.2	-$0.6	-$6.1	-$1.4	-$0.7	-$0.2	-$0.3	-$5.4	-$3.7	$0.0	-$2.4	-$2.5	-$0.6	-$0.6	-$4.8	-$0.7	-$0.1	-$1.3	-$0.8	-$1.8	-$1.6	-$0.4	-$0.7	-$0.1
2042	-$1.1	-$4.9	-$0.5	-$3.4	-$1.1	-$0.5	-$0.2	-$0.3	-$5.1	-$3.7	$0.1	-$1.5	-$2.1	-$0.5	-$0.4	-$2.9	-$0.6	$0.0	-$1.2	-$0.6	-$1.8	-$1.0	-$0.3	-$0.5	-$0.1
2043	-$1.4	-$5.0	-$0.6	-$5.0	-$1.9	-$0.6	-$0.3	-$0.3	-$5.5	-$4.2	$0.0	-$1.4	-$2.0	-$0.4	-$0.4	-$3.6	-$0.8	$0.0	-$1.4	-$0.7	-$1.7	-$0.7	-$0.4	-$0.5	-$0.1
2044	-$1.5	-$6.9	-$0.8	-$7.0	-$2.1	-$0.8	-$0.3	-$0.3	-$6.1	-$4.4	$0.0	-$3.5	-$3.2	-$0.7	-$0.7	-$4.4	-$0.9	-$0.1	-$1.4	-$0.9	-$2.6	-$1.5	-$0.5	-$1.2	-$0.1
2045	-$1.4	-$3.9	-$0.7	-$6.3	-$0.9	-$0.7	-$0.3	-$0.4	-$6.0	-$4.5	$0.1	-$2.9	-$3.1	-$0.7	-$0.7	-$5.4	-$0.9	$0.0	-$1.5	-$0.8	-$2.2	-$1.3	-$0.5	-$0.8	-$0.1
2046	-$1.6	-$4.6	-$0.8	-$7.0	-$1.8	-$0.8	-$0.3	-$0.4	-$6.5	-$4.9	$0.1	-$4.7	-$3.8	-$2.4	-$0.9	-$5.0	-$1.0	-$0.1	-$1.6	-$0.9	-$3.4	-$2.6	-$0.5	-$1.4	-$0.1
2047	-$1.9	-$4.3	-$1.0	-$5.0	-$1.6	-$1.0	-$0.4	-$0.5	-$7.3	-$5.6	$0.2	-$5.9	-$4.8	-$1.2	-$1.0	-$8.8	-$1.3	-$0.1	-$2.0	-$1.2	-$3.8	-$2.8	-$0.6	-$1.9	-$0.1
2048	-$1.9	-$2.8	-$0.9	-$0.5	-$0.8	-$0.8	-$0.3	-$0.5	-$7.1	-$5.7	$0.3	-$5.6	-$4.5	-$1.1	-$0.8	-$7.2	-$1.2	$0.0	-$1.9	-$0.9	-$3.7	-$1.6	-$0.6	-$1.5	$0.0
2049	-$1.8	-$4.5	-$0.9	-$0.5	-$0.2	-$0.5	-$0.3	-$0.4	-$6.9	-$5.5	$0.3	-$2.8	-$3.0	-$0.6	-$0.5	-$4.5	-$0.9	$0.0	-$1.6	-$0.6	-$2.9	-$1.0	-$0.5	-$0.6	$0.0
2050	-$2.2	-$5.8	-$1.2	-$2.5	-$2.4	-$0.9	-$0.3	-$0.5	-$7.8	-$6.2	$0.1	-$5.2	-$4.7	-$1.1	-$1.0	-$6.8	-$1.3	-$0.1	-$1.9	-$1.1	-$3.3	-$2.0	-$0.7	-$1.7	-$0.1

Table E-4. Change in GDP Contribution by State and Year (in Billions)

Change in GDP - 1% Case (Nebraska to Wyoming)

Year	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY	U.S.
2010	$0.0	$0.0	$0.0	$0.0	$0.0	-$0.1	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.5
2011	$0.0	$0.0	$0.0	-$0.1	$0.0	-$0.3	-$0.1	$0.0	$0.0	$0.0	$0.0	-$0.1	$0.0	$0.0	$0.0	-$0.1	-$0.2	$0.0	$0.0	-$0.1	$0.0	$0.0	$0.0	$0.0	-$1.4
2012	$0.0	-$0.2	$0.0	-$0.2	-$0.2	-$0.6	-$0.2	$0.0	-$0.1	-$0.7	$0.0	-$0.3	$0.0	-$0.1	$0.0	-$0.1	-$0.7	$0.0	$0.0	-$0.2	$0.0	$0.0	$0.0	-$0.1	-$5.8
2013	$0.0	-$0.4	$0.0	-$0.2	-$0.1	-$0.6	-$0.3	$0.0	-$0.1	-$0.1	$0.1	-$0.3	$0.0	-$0.1	$0.0	-$0.2	-$0.5	$0.0	$0.0	-$0.2	$0.1	$0.0	$0.0	$0.0	-$4.9
2014	$0.0	-$0.4	$0.0	-$0.3	-$0.2	-$0.9	-$0.4	$0.0	-$0.1	-$0.2	$0.0	-$0.5	$0.0	-$0.2	$0.0	-$0.2	-$0.9	$0.0	$0.0	-$0.3	$0.1	$0.0	$0.0	$0.0	-$8.0
2015	-$0.1	-$1.3	$0.0	-$0.6	-$1.2	-$1.7	-$0.5	$0.0	-$0.2	-$3.1	$0.0	-$0.7	$0.0	-$0.1	$0.0	-$0.4	-$2.1	-$0.5	$0.0	-$0.4	-$0.1	-$0.1	-$0.1	-$0.6	-$24.3
2016	-$0.1	-$1.6	$0.0	-$0.5	-$1.0	-$1.4	-$0.5	$0.0	-$0.2	-$0.4	$0.0	-$0.6	$0.0	-$0.1	$0.0	-$0.5	-$1.8	-$0.7	$0.0	-$0.4	$0.0	-$0.1	-$0.1	-$0.1	-$18.0
2017	-$0.1	-$0.5	$0.0	-$0.4	-$0.2	-$1.0	-$0.5	$0.0	-$0.1	-$0.7	$0.2	-$0.5	$0.0	-$0.1	$0.0	-$0.4	-$1.4	-$0.2	$0.0	-$0.4	$0.2	-$0.1	$0.0	-$0.1	-$11.8
2018	-$0.1	-$0.9	$0.0	-$0.6	-$1.2	-$2.0	-$0.7	$0.0	-$0.3	-$3.6	$0.1	-$0.8	$0.0	-$0.2	$0.0	-$0.6	-$2.5	-$0.4	$0.0	-$0.5	$0.1	-$0.1	-$0.1	-$0.5	-$25.7
2019	-$0.1	-$0.5	$0.0	-$0.4	-$0.2	-$1.1	-$0.7	$0.0	-$0.1	-$1.4	$0.1	-$0.6	$0.0	-$0.3	$0.0	-$0.5	-$1.8	-$0.2	$0.0	-$0.5	$0.2	-$0.1	$0.0	-$0.1	-$14.0
2020	$0.0	-$0.1	$0.0	-$0.3	-$0.2	-$1.0	-$0.6	$0.0	$0.0	-$0.4	$0.2	-$0.6	$0.0	-$0.2	$0.0	-$0.4	-$1.3	-$0.1	$0.0	-$0.4	$0.2	-$0.1	$0.0	$0.0	-$10.2
2021	-$0.1	-$1.4	$0.0	-$0.5	-$1.0	-$1.6	-$0.7	$0.0	-$0.1	-$0.4	$0.1	-$0.6	$0.0	-$0.2	$0.0	-$0.5	-$2.0	-$0.8	$0.0	-$0.5	$0.1	-$0.1	-$0.1	-$0.4	-$19.9
2022	-$0.1	-$0.5	$0.0	-$0.4	-$1.0	-$1.3	-$0.7	$0.0	-$0.1	-$1.4	$0.2	-$0.7	$0.0	-$0.2	$0.0	-$0.6	-$1.8	-$0.2	$0.0	-$0.5	$0.2	-$0.1	$0.0	-$0.1	-$15.7
2023	-$0.1	-$0.2	$0.0	-$0.5	-$1.3	-$1.6	-$0.7	$0.0	-$0.3	-$0.4	$0.2	-$0.6	$0.0	-$0.2	$0.0	-$0.5	-$1.9	-$0.2	$0.0	-$0.5	$0.2	-$0.1	$0.1	-$0.1	-$16.3
2024	$0.0	-$1.1	$0.0	-$0.4	-$0.6	-$1.2	-$0.7	$0.0	-$0.2	-$0.3	$0.3	-$0.7	$0.0	-$0.2	$0.0	-$0.5	-$1.7	-$0.2	$0.0	-$0.5	$0.3	-$0.1	$0.0	$0.0	-$13.3
2025	-$0.1	-$1.4	$0.0	-$0.5	-$0.7	-$1.7	-$0.8	$0.0	-$0.2	-$0.3	$0.1	-$0.9	$0.0	-$0.3	$0.0	-$0.6	-$1.7	-$0.4	$0.0	-$0.5	$0.1	-$0.1	$0.0	-$0.2	-$17.3
2026	-$0.1	-$2.0	$0.0	-$0.6	-$1.0	-$1.8	-$0.8	$0.0	-$0.3	-$0.3	$0.2	-$0.9	$0.0	-$0.3	$0.0	-$0.7	-$1.9	-$0.7	$0.0	-$0.6	$0.2	-$0.1	$0.0	-$0.1	-$20.4
2027	-$0.1	-$2.5	$0.0	-$0.7	-$0.9	-$2.3	-$0.8	$0.0	-$0.4	-$0.6	$0.8	-$1.0	$0.0	-$0.2	$0.0	-$0.9	-$2.1	-$0.8	$0.0	-$0.7	$0.2	-$1.2	$0.0	-$0.2	-$24.9
2028	-$0.1	-$1.4	$0.0	-$0.8	-$1.3	-$2.6	-$1.1	$0.0	-$0.6	-$2.7	$0.2	-$1.1	$0.0	-$0.4	$0.0	-$1.2	-$2.7	-$0.3	$0.0	-$0.9	$0.3	-$1.6	-$0.1	-$0.1	-$30.4
2029	-$0.2	-$2.5	-$0.1	-$1.2	-$1.7	-$4.1	-$1.3	-$0.1	-$1.0	-$2.6	$0.1	-$1.6	$0.0	-$0.4	-$0.1	-$1.5	-$4.4	-$1.4	$0.0	-$1.2	$0.0	-$2.7	-$0.2	-$0.9	-$50.4
2030	-$0.1	-$1.0	$0.0	-$1.0	-$1.6	-$3.1	-$1.2	$0.0	-$1.1	-$2.9	$0.2	-$1.4	$0.0	-$0.5	$0.0	-$1.2	-$3.6	-$0.6	$0.0	-$1.1	$0.2	-$2.1	-$0.1	-$0.2	-$38.4
2031	-$0.1	-$1.2	$0.0	-$0.8	-$1.2	-$2.5	-$1.1	$0.0	-$0.5	-$2.3	$0.3	-$1.2	$0.0	-$0.3	$0.0	-$1.4	-$3.3	-$0.5	$0.0	-$0.9	$0.4	-$0.6	-$0.1	-$0.1	-$30.8
2032	-$0.1	-$1.2	$0.0	-$0.9	-$1.0	-$2.9	-$1.4	-$0.1	-$1.2	-$1.0	$0.3	-$1.4	$0.0	-$0.5	$0.0	-$1.5	-$3.5	-$0.5	$0.0	-$1.1	$0.4	-$2.3	-$0.1	-$0.2	-$33.5
2033	-$0.1	-$0.6	$0.0	-$1.0	-$1.2	-$3.1	-$1.5	$0.0	-$1.2	-$2.7	$0.3	-$1.4	$0.0	-$0.5	$0.0	-$1.8	-$3.8	-$0.3	$0.0	-$1.2	$0.4	-$1.7	-$0.2	-$0.1	-$37.1
2034	-$0.1	-$2.1	$0.0	-$0.8	-$0.8	-$2.8	-$1.5	-$0.1	-$0.6	-$0.7	$0.3	-$1.4	$0.0	-$0.5	$0.0	-$1.6	-$3.5	-$1.0	$0.0	-$1.1	$0.4	-$0.3	-$0.4	-$0.8	-$34.2
2035	-$0.2	-$2.3	-$0.1	-$1.4	-$1.5	-$5.1	-$1.9	-$0.1	-$2.0	-$3.6	$0.3	-$1.9	$0.0	-$0.7	-$0.1	-$2.2	-$4.9	-$1.0	-$0.1	-$1.6	$0.3	-$3.6	-$0.3	-$0.2	-$61.3
2036	-$0.3	-$2.5	-$0.1	-$1.5	-$1.4	-$5.4	-$2.0	-$0.1	-$2.5	-$2.5	$0.3	-$2.1	$0.0	-$0.7	-$0.1	-$2.4	-$5.5	-$1.3	$0.0	-$1.7	$0.3	-$3.7	-$0.5	-$0.5	-$68.0
2037	-$0.2	-$2.4	$0.0	-$0.9	-$1.2	-$3.4	-$1.6	-$0.1	-$0.8	-$0.9	$0.4	-$1.6	$0.0	-$0.7	$0.0	-$1.6	-$4.7	-$1.3	$0.0	-$1.2	$0.4	-$0.6	-$0.5	-$0.2	-$45.9
2038	-$0.2	-$1.9	$0.0	-$1.1	-$1.0	-$3.9	-$1.7	-$0.1	-$1.3	-$1.3	$0.5	-$1.8	$0.0	-$0.7	$0.0	-$2.0	-$4.3	-$1.0	$0.0	-$1.4	$0.7	-$3.0	-$0.5	-$0.2	-$48.6
2039	-$0.2	-$1.5	$0.0	-$1.2	-$0.9	-$4.3	-$1.9	-$0.1	-$2.2	-$1.7	$0.6	-$2.0	$0.0	-$0.8	$0.0	-$2.2	-$4.1	-$0.5	$0.0	-$1.6	$0.9	-$3.4	-$0.4	-$0.1	-$50.1
2040	-$0.3	-$3.6	-$0.1	-$1.6	-$1.7	-$6.0	-$2.2	-$0.1	-$2.9	-$1.5	$0.6	-$2.5	$0.0	-$0.8	-$0.1	-$2.9	-$5.4	-$1.7	-$0.1	-$1.9	$0.8	-$5.0	-$0.6	-$0.3	-$74.3
2041	-$0.4	-$3.4	-$0.1	-$2.1	-$1.3	-$7.6	-$2.5	-$0.3	-$3.7	-$1.8	$0.6	-$3.2	-$0.1	-$0.9	-$0.1	-$3.3	-$6.0	-$1.4	-$0.1	-$2.4	$0.7	-$7.3	-$0.9	-$0.6	-$90.3
2042	-$0.3	-$2.0	-$0.1	-$1.8	-$1.3	-$6.4	-$2.6	-$0.1	-$3.3	-$1.1	$0.7	-$3.0	$0.0	-$0.9	-$0.1	-$3.1	-$5.6	-$1.7	-$0.1	-$2.2	$0.9	-$6.6	-$0.8	-$0.7	-$76.6
2043	-$0.3	-$2.5	-$0.1	-$2.1	-$1.6	-$7.3	-$2.9	-$0.1	-$3.6	-$1.3	$0.7	-$3.4	-$0.1	-$1.0	-$0.1	-$3.2	-$6.4	-$1.9	-$0.1	-$2.5	$0.8	-$6.3	-$0.6	-$0.6	-$85.6
2044	-$0.4	-$4.1	-$0.1	-$2.3	-$1.9	-$8.5	-$3.0	-$0.2	-$3.8	-$2.5	$0.7	-$3.7	-$0.1	-$1.1	-$0.1	-$3.9	-$7.6	-$2.6	-$0.1	-$2.6	$0.7	-$5.1	-$1.2	-$1.0	-$106.2
2045	-$0.4	-$3.7	-$0.1	-$2.3	-$1.2	-$8.3	-$3.2	-$0.2	-$4.6	-$2.0	$0.9	-$3.8	-$0.1	-$1.1	-$0.1	-$4.1	-$7.2	-$1.7	-$0.1	-$2.9	$1.0	-$9.4	-$1.0	-$0.6	-$101.8
2046	-$0.6	-$3.7	-$0.2	-$2.4	-$1.7	-$9.1	-$3.4	-$0.3	-$4.6	-$2.9	$0.9	-$3.8	-$0.1	-$1.3	-$0.2	-$4.3	-$8.1	-$2.0	-$0.1	-$2.9	$1.1	-$6.7	-$1.6	-$1.1	-$116.1
2047	-$0.6	-$2.2	-$0.2	-$3.0	-$1.4	-$10.8	-$4.0	-$0.3	-$6.1	-$3.3	$1.0	-$4.7	-$0.1	-$1.5	-$0.2	-$4.9	-$9.1	-$1.7	-$0.1	-$3.6	$1.3	-$10.4	-$2.1	-$0.5	-$132.1
2048	-$0.5	-$0.5	-$0.2	-$2.7	-$1.6	-$9.5	-$4.0	-$0.2	-$5.9	-$2.9	$1.2	-$4.6	-$0.1	-$1.5	-$0.1	-$4.9	-$8.5	-$1.0	-$0.1	-$3.5	$1.6	-$10.1	-$1.9	-$0.4	-$113.5
2049	-$0.3	-$1.2	-$0.1	-$2.1	-$1.6	-$7.4	-$3.7	-$0.1	-$4.6	-$2.4	$1.2	-$3.8	$0.0	-$1.4	-$0.1	-$4.6	-$7.6	-$1.1	-$0.1	-$3.0	$1.7	-$8.0	-$1.3	-$0.3	-$92.7
2050	-$0.6	-$2.4	-$0.2	-$2.9	-$2.4	-$10.4	-$4.2	-$0.2	-$5.8	-$3.6	$1.1	-$4.8	-$0.1	-$1.6	-$0.2	-$5.3	-$9.8	-$1.8	-$0.2	-$3.6	$1.3	-$9.3	-$1.8	-$0.9	-$130.0

Table E-5. Change in Employment by State (1% Case)

Change in Employment (1K Labor Years) - 1% Case

Region	2010	2020	2030	2040	2050
United States	**-0.7**	**-104.5**	**-307.1**	**-474.3**	**-688.7**
Alabama	-0.2	-2.9	-5.3	-7.7	-13.6
Arizona	1.5	-4.6	-20.1	-33.7	-30.4
Arkansas	0.0	-1.2	-2.5	-3.9	-7.2
California	2.0	-3.9	-15.5	-31.8	-7.6
Colorado	0.2	-0.6	-11.8	-9.1	-12.5
Connecticut	0.0	-0.3	-1.2	-1.9	-2.9
Delaware	0.0	-0.4	-0.8	-1.1	-1.6
D.C.	0.0	-0.1	-0.5	-0.9	-1.5
Florida	-1.6	-19.3	-28.5	-37.0	-49.2
Georgia	-0.6	-11.2	-16.5	-22.1	-32.4
Idaho	0.0	0.3	0.1	0.4	0.8
Illinois	0.2	1.3	-0.1	-6.1	-24.0
Indiana	0.0	0.1	-4.2	-13.2	-25.8
Iowa	0.1	0.6	-0.4	-2.4	-6.3
Kansas	0.1	-0.7	-2.0	-2.8	-6.3
Kentucky	-0.1	-2.0	-4.9	-21.1	-40.3
Louisiana	0.0	-1.5	-3.5	-4.7	-8.2
Maine	0.0	0.0	-0.2	-0.3	-0.5
Maryland	-0.2	-2.1	-4.6	-6.5	-10.0
Massachusetts	0.0	-0.3	-1.6	-2.4	-4.1
Michigan	0.0	-0.5	-2.4	-8.4	-15.8
Minnesota	0.2	0.2	-0.8	-3.7	-9.2
Mississippi	0.0	-0.5	-1.5	-2.5	-4.8
Missouri	0.1	0.1	-1.0	-2.7	-9.2
Montana	0.0	0.2	-0.1	-0.3	-0.5
Nebraska	0.1	-0.2	-1.0	-2.0	-3.3
Nevada	0.3	-1.1	-6.4	-18.8	-10.3
New Hampshire	0.0	-0.1	-0.3	-0.6	-1.0
New Jersey	-0.4	-2.6	-5.7	-7.9	-11.5
New Mexico	0.0	-2.3	-14.9	-12.7	-15.4
New York	-0.7	-6.7	-15.0	-22.9	-32.9
North Carolina	-0.4	-7.2	-11.5	-16.2	-24.6
North Dakota	0.0	-0.1	-0.4	-0.7	-1.2
Ohio	0.0	-0.1	-8.6	-19.3	-32.4
Oklahoma	0.1	-4.5	-25.2	-11.1	-23.7
Oregon	0.1	2.0	2.4	4.6	6.4
Pennsylvania	-0.5	-5.7	-11.9	-17.4	-26.2
Rhode Island	0.0	0.0	-0.2	-0.2	-0.4
South Carolina	-0.1	-3.4	-5.3	-7.3	-11.2
South Dakota	0.0	0.1	-0.3	-0.5	-1.0
Tennessee	-0.2	-4.9	-10.7	-21.4	-31.3
Texas	-0.4	-14.2	-31.8	-36.0	-53.8
Utah	0.1	-1.4	-5.1	-12.3	-10.6
Vermont	0.0	0.0	-0.3	-0.8	-1.2
Virginia	-0.4	-4.3	-8.9	-12.5	-18.7
Washington	0.1	2.3	2.6	5.9	7.6
West Virginia	0.0	-0.7	-17.2	-33.7	-54.2
Wisconsin	0.2	0.0	-0.5	-3.5	-9.5
Wyoming	0.0	-0.4	-1.5	-1.9	-5.6

Table E-6. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Accommodation and Food Services ($M)

Region	2020	2030	2040	2050
United States	**-$383.2**	**-$804.3**	**-$1,311.1**	**-$1,758.0**
Alabama	-$8.6	-$13.5	-$23.3	-$45.3
Arizona	-$9.8	-$50.2	-$90.6	-$83.2
Arkansas	-$1.2	-$2.4	-$6.1	-$13.5
California	$0.0	-$29.4	-$142.0	$149.4
Colorado	$4.9	-$8.6	$0.0	-$3.7
Connecticut	$7.3	$11.0	$14.7	$23.3
Delaware	-$1.2	-$1.2	-$2.4	-$2.4
District of Columbia	$2.4	$2.4	$1.2	$0.0
Florida	-$151.8	-$225.3	-$318.3	-$466.4
Georgia	-$53.9	-$77.1	-$111.4	-$173.8
Idaho	$2.4	$2.4	$6.1	$8.6
Illinois	$7.3	$11.0	$4.9	-$28.2
Indiana	$3.7	$3.7	-$6.1	-$23.3
Iowa	$1.2	$1.2	-$1.2	-$6.1
Kansas	-$1.2	-$1.2	-$2.4	-$7.3
Kentucky	-$8.6	-$15.9	-$38.0	-$77.1
Louisiana	-$4.9	-$7.3	-$9.8	-$24.5
Maine	$1.2	$1.2	$2.4	$2.4
Maryland	-$8.6	-$13.5	-$17.1	-$26.9
Massachusetts	$4.9	$7.3	$9.8	$13.5
Michigan	$0.0	$0.0	-$7.3	-$18.4
Minnesota	$0.0	$1.2	-$2.4	-$12.2
Mississippi	-$1.2	-$2.4	-$7.3	-$17.1
Missouri	$2.4	$4.9	$4.9	-$7.3
Montana	$1.2	$1.2	$2.4	$2.4
Nebraska	$0.0	$0.0	-$2.4	-$3.7
Nevada	$1.2	-$15.9	-$56.3	-$53.9
New Hampshire	$1.2	$1.2	$1.2	$2.4
New Jersey	$1.2	-$2.4	$0.0	$1.2
New Mexico	-$4.9	-$24.5	-$25.7	-$31.8
New York	-$23.3	-$38.0	-$51.4	-$60.0
North Carolina	-$25.7	-$40.4	-$58.8	-$89.4
North Dakota	$0.0	$0.0	-$1.2	-$2.4
Ohio	$6.1	$2.4	-$7.3	-$24.5
Oklahoma	-$12.2	-$34.3	-$29.4	-$51.4
Oregon	$8.6	$12.2	$25.7	$35.5
Pennsylvania	-$18.4	-$34.3	-$45.3	-$66.1
Rhode Island	$1.2	$1.2	$2.4	$3.7
South Carolina	-$22.0	-$33.1	-$51.4	-$88.1
South Dakota	$0.0	$0.0	-$1.2	-$2.4
Tennessee	-$19.6	-$33.1	-$62.4	-$110.2
Texas	-$60.0	-$138.3	-$161.6	-$273.0
Utah	$0.0	-$7.3	-$18.4	-$18.4
Vermont	$0.0	$0.0	$0.0	$0.0
Virginia	-$19.6	-$31.8	-$42.8	-$63.7
Washington	$14.7	$20.8	$45.3	$58.8
West Virginia	-$3.7	-$18.4	-$39.2	-$73.5
Wisconsin	$0.0	$1.2	-$2.4	-$12.2
Wyoming	$0.0	-$1.2	-$2.4	-$7.3

Table E-7. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Administrative and Waste Services ($M)

Region	2020	2030	2040	2050
United States	**-$252.2**	**-$1,001.4**	**-$1,734.7**	**-$2,634.5**
Alabama	-$4.9	-$11.0	-$18.4	-$31.8
Arizona	-$14.7	-$74.7	-$138.3	-$148.1
Arkansas	-$1.2	-$3.7	-$6.1	-$11.0
California	-$15.9	-$72.2	-$159.1	-$102.8
Colorado	-$4.9	-$42.8	-$39.2	-$58.8
Connecticut	-$2.4	-$7.3	-$12.2	-$19.6
Delaware	-$1.2	-$2.4	-$3.7	-$7.3
District of Columbia	-$1.2	-$4.9	-$8.6	-$14.7
Florida	-$56.3	-$123.6	-$193.4	-$293.8
Georgia	-$26.9	-$53.9	-$84.5	-$132.2
Idaho	$0.0	-$1.2	-$1.2	$0.0
Illinois	$6.1	-$3.7	-$38.0	-$115.1
Indiana	$1.2	-$11.0	-$35.5	-$72.2
Iowa	$6.1	$1.2	-$4.9	-$13.5
Kansas	$0.0	-$6.1	-$8.6	-$19.6
Kentucky	-$1.2	-$8.6	-$35.5	-$69.8
Louisiana	-$2.4	-$9.8	-$14.7	-$26.9
Maine	$0.0	$0.0	-$1.2	-$1.2
Maryland	-$6.1	-$18.4	-$29.4	-$50.2
Massachusetts	-$2.4	-$9.8	-$17.1	-$33.1
Michigan	-$1.2	-$15.9	-$46.5	-$88.1
Minnesota	$4.9	-$1.2	-$12.2	-$31.8
Mississippi	-$1.2	-$2.4	-$4.9	-$9.8
Missouri	$1.2	-$3.7	-$9.8	-$29.4
Montana	$0.0	$0.0	-$1.2	-$1.2
Nebraska	$4.9	$0.0	-$3.7	-$8.6
Nevada	-$3.7	-$22.0	-$62.4	-$38.0
New Hampshire	$0.0	-$1.2	-$2.4	-$6.1
New Jersey	-$11.0	-$30.6	-$51.4	-$80.8
New Mexico	-$4.9	-$34.3	-$31.8	-$42.8
New York	-$19.6	-$58.8	-$106.5	-$170.2
North Carolina	-$13.5	-$29.4	-$47.7	-$78.4
North Dakota	$1.2	$0.0	-$1.2	-$2.4
Ohio	-$1.2	-$29.4	-$68.6	-$123.6
Oklahoma	-$7.3	-$60.0	-$30.6	-$63.7
Oregon	$3.7	$4.9	$9.8	$15.9
Pennsylvania	-$11.0	-$31.8	-$52.6	-$83.2
Rhode Island	$0.0	-$1.2	-$1.2	-$2.4
South Carolina	-$7.3	-$15.9	-$23.3	-$36.7
South Dakota	$1.2	$0.0	$0.0	-$1.2
Tennessee	-$9.8	-$29.4	-$62.4	-$100.4
Texas	-$38.0	-$112.6	-$145.7	-$235.1
Utah	-$3.7	-$14.7	-$36.7	-$36.7
Vermont	$0.0	$0.0	-$1.2	-$1.2
Virginia	-$9.8	-$25.7	-$42.8	-$68.6
Washington	$2.4	$0.0	$6.1	$11.0
West Virginia	-$1.2	-$19.6	-$41.6	-$66.1
Wisconsin	$1.2	-$1.2	-$9.8	-$25.7
Wyoming	$0.0	-$1.2	-$2.4	-$6.1

Table E-8. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Arts, Entertainment, and Recreation ($M)

Region	2020	2030	2040	2050	Region	2020	2030	2040	2050
United States	**-$74.7**	**-$307.3**	**-$695.4**	**-$1,235.2**	Montana	$0.0	$0.0	-$1.2	-$1.2
Alabama	-$1.2	-$2.4	-$4.9	-$12.2	Nebraska	$0.0	$0.0	-$1.2	-$3.7
Arizona	-$4.9	-$24.5	-$55.1	-$63.7	Nevada	-$2.4	-$13.5	-$49.0	-$35.5
Arkansas	$0.0	-$1.2	-$2.4	-$4.9	New Hampshire	$0.0	$0.0	$0.0	-$1.2
California	-$3.7	-$25.7	-$62.4	-$11.0	New Jersey	-$2.4	-$4.9	-$9.8	-$18.4
Colorado	-$1.2	-$19.6	-$24.5	-$40.4	New Mexico	-$1.2	-$8.6	-$12.2	-$17.1
Connecticut	$0.0	-$1.2	-$2.4	-$3.7	New York	-$7.3	-$19.6	-$38.0	-$66.1
Delaware	$0.0	-$1.2	-$2.4	-$4.9	North Carolina	-$4.9	-$11.0	-$22.0	-$41.6
District of Columbia	$0.0	-$1.2	-$1.2	-$3.7	North Dakota	$0.0	$0.0	$0.0	-$1.2
Florida	-$22.0	-$56.3	-$110.2	-$198.3	Ohio	$0.0	-$6.1	-$24.5	-$57.5
Georgia	-$6.1	-$12.2	-$23.3	-$42.8	Oklahoma	-$2.4	-$14.7	-$11.0	-$28.2
Idaho	$0.0	$0.0	$1.2	$3.7	Oregon	$1.2	$3.7	$7.3	$14.7
Illinois	$2.4	$2.4	-$6.1	-$47.7	Pennsylvania	-$3.7	-$11.0	-$22.0	-$42.8
Indiana	$0.0	-$4.9	-$23.3	-$66.1	Rhode Island	$0.0	$0.0	$0.0	$0.0
Iowa	$1.2	$0.0	-$2.4	-$9.8	South Carolina	-$2.4	-$4.9	-$9.8	-$20.8
Kansas	$0.0	-$1.2	-$1.2	-$4.9	South Dakota	$0.0	$0.0	-$1.2	-$2.4
Kentucky	$0.0	-$2.4	-$15.9	-$42.8	Tennessee	-$2.4	-$8.6	-$23.3	-$44.1
Louisiana	-$1.2	-$7.3	-$13.5	-$28.2	Texas	-$8.6	-$25.7	-$40.4	-$75.9
Maine	$0.0	$0.0	$0.0	$0.0	Utah	-$1.2	-$4.9	-$17.1	-$20.8
Maryland	-$1.2	-$4.9	-$8.6	-$18.4	Vermont	$0.0	$0.0	$0.0	-$1.2
Massachusetts	$0.0	$0.0	$0.0	-$1.2	Virginia	-$2.4	-$7.3	-$14.7	-$29.4
Michigan	$0.0	-$1.2	-$13.5	-$36.7	Washington	$2.4	$6.1	$15.9	$29.4
Minnesota	$1.2	$1.2	-$3.7	-$14.7	West Virginia	$0.0	-$9.8	-$30.6	-$67.3
Mississippi	$0.0	-$1.2	-$3.7	-$8.6	Wisconsin	$0.0	$1.2	-$2.4	-$12.2
Missouri	$0.0	-$2.4	-$7.3	-$26.9	Wyoming	$0.0	-$1.2	-$2.4	-$6.1

Table E-9. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Construction ($M)

Region	2020	2030	2040	2050
United States	**-$694.1**	**-$1,581.7**	**-$1,658.8**	**-$2,196.3**
Alabama	-$12.2	-$18.4	-$19.6	-$35.5
Arizona	-$52.6	-$115.1	-$134.7	-$104.1
Arkansas	-$4.9	-$7.3	-$8.6	-$14.7
California	-$40.4	-$115.1	-$153.0	-$7.3
Colorado	-$12.2	-$83.2	-$23.3	-$38.0
Connecticut	-$3.7	-$8.6	-$7.3	-$11.0
Delaware	-$2.4	-$4.9	-$4.9	-$7.3
District of Columbia	$0.0	-$1.2	-$1.2	-$2.4
Florida	-$113.9	-$139.6	-$143.2	-$195.9
Georgia	-$47.7	-$56.3	-$61.2	-$94.3
Idaho	$0.0	-$1.2	$2.4	$3.7
Illinois	-$1.2	-$18.4	-$49.0	-$124.9
Indiana	-$2.4	-$23.3	-$60.0	-$97.9
Iowa	$1.2	-$3.7	-$11.0	-$19.6
Kansas	-$6.1	-$11.0	-$4.9	-$15.9
Kentucky	-$6.1	-$20.8	-$58.8	-$95.5
Louisiana	-$11.0	-$20.8	-$18.4	-$35.5
Maine	-$1.2	-$1.2	-$1.2	-$1.2
Maryland	-$17.1	-$33.1	-$35.5	-$53.9
Massachusetts	-$4.9	-$11.0	-$9.8	-$17.1
Michigan	-$3.7	-$12.2	-$30.6	-$56.3
Minnesota	$0.0	-$6.1	-$19.6	-$30.6
Mississippi	-$3.7	-$6.1	-$6.1	-$12.2
Missouri	-$3.7	-$9.8	-$15.9	-$39.2

Region	2020	2030	2040	2050
Montana	$0.0	-$1.2	-$1.2	-$1.2
Nebraska	-$2.4	-$3.7	-$4.9	-$7.3
Nevada	-$24.5	-$71.0	-$95.5	-$23.3
New Hampshire	-$1.2	-$2.4	-$2.4	-$3.7
New Jersey	-$17.1	-$29.4	-$31.8	-$45.3
New Mexico	-$14.7	-$62.4	-$24.5	-$36.7
New York	-$28.2	-$55.1	-$69.8	-$96.7
North Carolina	-$33.1	-$44.1	-$47.7	-$74.7
North Dakota	$0.0	-$1.2	-$2.4	-$2.4
Ohio	-$3.7	-$41.6	-$69.8	-$105.3
Oklahoma	-$31.8	-$82.0	-$6.1	-$45.3
Oregon	$6.1	$3.7	$13.5	$17.1
Pennsylvania	-$26.9	-$50.2	-$56.3	-$79.6
Rhode Island	-$1.2	-$1.2	-$1.2	-$1.2
South Carolina	-$17.1	-$20.8	-$23.3	-$35.5
South Dakota	$0.0	-$1.2	-$1.2	-$2.4
Tennessee	-$20.8	-$46.5	-$61.2	-$86.9
Texas	-$85.7	-$156.7	-$106.5	-$183.6
Utah	-$12.2	-$35.5	-$41.6	-$23.3
Vermont	$0.0	-$1.2	-$2.4	-$3.7
Virginia	-$25.7	-$49.0	-$51.4	-$75.9
Washington	$7.3	$0.0	$22.0	$20.8
West Virginia	-$3.7	-$74.7	-$94.3	-$134.7
Wisconsin	-$1.2	-$6.1	-$17.1	-$38.0
Wyoming	-$4.9	-$15.9	-$2.4	-$14.7

Table E-10. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Educational Services ($M)

Region	2020	2030	2040	2050
United States	**-$15.9**	**-$93.0**	**-$202.0**	**-$345.2**
Alabama	$0.0	-$1.2	-$2.4	-$3.7
Arizona	-$2.4	-$8.6	-$17.1	-$17.1
Arkansas	$0.0	$0.0	-$1.2	-$1.2
California	$2.4	-$1.2	-$6.1	$11.0
Colorado	$0.0	-$3.7	-$3.7	-$4.9
Connecticut	$0.0	-$1.2	-$2.4	-$4.9
Delaware	$0.0	$0.0	$0.0	-$1.2
District of Columbia	$0.0	-$2.4	-$3.7	-$7.3
Florida	-$4.9	-$9.8	-$15.9	-$22.0
Georgia	-$2.4	-$6.1	-$11.0	-$18.4
Idaho	$0.0	$0.0	$0.0	$0.0
Illinois	$2.4	$2.4	-$1.2	-$17.1
Indiana	$0.0	-$1.2	-$4.9	-$11.0
Iowa	$0.0	$0.0	-$1.2	-$2.4
Kansas	$0.0	$0.0	-$1.2	-$1.2
Kentucky	$0.0	-$1.2	-$3.7	-$8.6
Louisiana	$0.0	-$1.2	-$2.4	-$3.7
Maine	$0.0	$0.0	$0.0	-$1.2
Maryland	-$1.2	-$2.4	-$6.1	-$11.0
Massachusetts	$0.0	-$1.2	-$4.9	-$11.0
Michigan	$0.0	$0.0	-$2.4	-$7.3
Minnesota	$1.2	$1.2	$0.0	-$3.7
Mississippi	$0.0	$0.0	-$1.2	-$1.2
Missouri	$0.0	$0.0	-$2.4	-$7.3
Montana	$0.0	$0.0	$0.0	$0.0
Nebraska	$0.0	$0.0	$0.0	-$1.2
Nevada	$0.0	-$1.2	-$3.7	-$2.4
New Hampshire	$0.0	$0.0	-$1.2	-$2.4
New Jersey	$0.0	-$2.4	-$4.9	-$8.6
New Mexico	$0.0	-$3.7	-$3.7	-$4.9
New York	-$2.4	-$9.8	-$20.8	-$36.7
North Carolina	-$1.2	-$4.9	-$8.6	-$14.7
North Dakota	$0.0	$0.0	$0.0	$0.0
Ohio	$0.0	-$2.4	-$8.6	-$18.4
Oklahoma	-$1.2	-$4.9	-$3.7	-$6.1
Oregon	$1.2	$1.2	$3.7	$4.9
Pennsylvania	-$2.4	-$8.6	-$18.4	-$35.5
Rhode Island	$0.0	$0.0	-$1.2	-$1.2
South Carolina	$0.0	-$1.2	-$2.4	-$3.7
South Dakota	$0.0	$0.0	$0.0	$0.0
Tennessee	-$1.2	-$3.7	-$8.6	-$15.9
Texas	-$3.7	-$8.6	-$12.2	-$19.6
Utah	$0.0	-$2.4	-$6.1	-$6.1
Vermont	$0.0	$0.0	-$1.2	-$1.2
Virginia	-$1.2	-$3.7	-$6.1	-$11.0
Washington	$1.2	$2.4	$3.7	$4.9
West Virginia	$0.0	-$1.2	-$2.4	-$4.9
Wisconsin	$0.0	$0.0	-$1.2	-$4.9
Wyoming	$0.0	$0.0	$0.0	$0.0

Table E-11. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Finance and Insurance ($M)

Region	2020	2030	2040	2050
United States	**-$882.7**	**-$3,500.0**	**-$6,563.0**	**-$10,065.5**
Alabama	-$9.8	-$23.3	-$36.7	-$64.9
Arizona	-$20.8	-$127.3	-$254.6	-$254.6
Arkansas	-$3.7	-$9.8	-$13.5	-$24.5
California	-$55.1	-$192.2	-$468.9	-$395.4
Colorado	-$3.7	-$106.5	-$101.6	-$142.0
Connecticut	-$31.8	-$128.5	-$235.1	-$362.4
Delaware	-$7.3	-$24.5	-$42.8	-$68.6
District of Columbia	-$4.9	-$12.2	-$22.0	-$34.3
Florida	-$80.8	-$148.1	-$217.9	-$311.0
Georgia	-$46.5	-$88.1	-$133.4	-$206.9
Idaho	$0.0	-$1.2	-$2.4	-$2.4
Illinois	-$8.6	-$71.0	-$180.0	-$433.4
Indiana	-$2.4	-$23.3	-$62.4	-$120.0
Iowa	-$1.2	-$14.7	-$26.9	-$53.9
Kansas	-$2.4	-$13.5	-$17.1	-$38.0
Kentucky	-$6.1	-$19.6	-$83.2	-$146.9
Louisiana	-$4.9	-$13.5	-$20.8	-$35.5
Maine	-$1.2	-$3.7	-$6.1	-$8.6
Maryland	-$17.1	-$51.4	-$85.7	-$132.2
Massachusetts	-$30.6	-$118.7	-$209.3	-$315.8
Michigan	-$4.9	-$23.3	-$63.7	-$112.6
Minnesota	-$6.1	-$26.9	-$57.5	-$122.4
Mississippi	-$2.4	-$6.1	-$11.0	-$19.6
Missouri	-$2.4	-$17.1	-$30.6	-$75.9

Region	2020	2030	2040	2050
Montana	$0.0	-$2.4	-$3.7	-$4.9
Nebraska	-$3.7	-$11.0	-$17.1	-$28.2
Nevada	-$1.2	-$23.3	-$93.0	-$53.9
New Hampshire	-$2.4	-$9.8	-$15.9	-$23.3
New Jersey	-$40.4	-$142.0	-$252.2	-$378.3
New Mexico	-$2.4	-$39.2	-$36.7	-$49.0
New York	-$279.1	-$1,248.7	-$2,585.6	-$4,178.3
North Carolina	-$35.5	-$83.2	-$140.8	-$225.3
North Dakota	$0.0	-$2.4	-$3.7	-$6.1
Ohio	-$7.3	-$66.1	-$145.7	-$239.9
Oklahoma	-$3.7	-$83.2	-$31.8	-$82.0
Oregon	$4.9	$3.7	$9.8	$13.5
Pennsylvania	-$34.3	-$107.7	-$188.5	-$293.8
Rhode Island	-$1.2	-$6.1	-$9.8	-$15.9
South Carolina	-$8.6	-$19.6	-$30.6	-$50.2
South Dakota	$0.0	-$4.9	-$8.6	-$13.5
Tennessee	-$19.6	-$51.4	-$111.4	-$166.5
Texas	-$67.3	-$204.4	-$243.6	-$386.9
Utah	-$4.9	-$24.5	-$71.0	-$66.1
Vermont	$0.0	-$2.4	-$4.9	-$7.3
Virginia	-$22.0	-$64.9	-$109.0	-$170.2
Washington	$4.9	$2.4	$12.2	$14.7
West Virginia	-$1.2	-$26.9	-$57.5	-$83.2
Wisconsin	-$2.4	-$13.5	-$33.1	-$69.8
Wyoming	$0.0	-$2.4	-$4.9	-$13.5

Table E-12. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Forestry, Fishing, Related Activities, and Other ($M)

Region	2020	2030	2040	2050
United States	**-$15.9**	**-$31.8**	**-$31.8**	**-$29.4**
Alabama	-$1.2	-$1.2	-$1.2	-$1.2
Arizona	$0.0	-$1.2	-$1.2	-$1.2
Arkansas	$0.0	-$1.2	-$1.2	-$1.2
California	-$2.4	-$4.9	-$7.3	-$1.2
Colorado	$0.0	$0.0	$0.0	$0.0
Connecticut	$0.0	$0.0	$0.0	$0.0
Delaware	$0.0	$0.0	$0.0	$0.0
District of Columbia	$1.2	$1.2	$1.2	$1.2
Florida	-$3.7	-$4.9	-$6.1	-$8.6
Georgia	-$2.4	-$3.7	-$2.4	-$2.4
Idaho	$0.0	$0.0	$0.0	$0.0
Illinois	$0.0	$0.0	$0.0	$0.0
Indiana	$0.0	$0.0	$0.0	$0.0
Iowa	$0.0	$0.0	$0.0	$0.0
Kansas	$0.0	$0.0	$0.0	$0.0
Kentucky	$0.0	$0.0	-$1.2	-$1.2
Louisiana	-$1.2	-$1.2	-$1.2	-$1.2
Maine	$0.0	-$1.2	$0.0	$0.0
Maryland	$0.0	$0.0	$0.0	$0.0
Massachusetts	$0.0	-$1.2	$0.0	$0.0
Michigan	$0.0	$0.0	$0.0	$0.0
Minnesota	$0.0	$0.0	$0.0	$0.0
Mississippi	$0.0	-$1.2	-$1.2	-$1.2
Missouri	$0.0	$0.0	$0.0	$0.0
Montana	$0.0	$0.0	$0.0	$0.0
Nebraska	$0.0	$0.0	$0.0	$0.0
Nevada	$0.0	$0.0	$0.0	$0.0
New Hampshire	$0.0	$0.0	$0.0	$0.0
New Jersey	$0.0	$0.0	$0.0	$0.0
New Mexico	$0.0	$0.0	$0.0	$0.0
New York	-$1.2	-$1.2	-$2.4	-$3.7
North Carolina	-$1.2	-$1.2	-$1.2	-$1.2
North Dakota	$0.0	$0.0	$0.0	$0.0
Ohio	$0.0	$0.0	$0.0	$0.0
Oklahoma	$0.0	$0.0	$0.0	-$1.2
Oregon	$0.0	-$1.2	$0.0	$1.2
Pennsylvania	$0.0	-$1.2	-$1.2	-$1.2
Rhode Island	$0.0	$0.0	$0.0	$0.0
South Carolina	-$1.2	-$1.2	-$1.2	-$1.2
South Dakota	$0.0	$0.0	$0.0	$0.0
Tennessee	$0.0	$0.0	$0.0	-$1.2
Texas	-$2.4	-$3.7	-$3.7	-$4.9
Utah	$0.0	$0.0	$0.0	$0.0
Vermont	$0.0	$0.0	$0.0	$0.0
Virginia	$0.0	-$1.2	-$1.2	-$1.2
Washington	$0.0	$0.0	$1.2	$2.4
West Virginia	$0.0	$0.0	$0.0	$1.2
Wisconsin	$0.0	$0.0	$0.0	$0.0
Wyoming	$0.0	$0.0	$0.0	$0.0

Table E-13. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Health Care and Social Assistance ($M)

Region	2020	2030	2040	2050
United States	**-$530.1**	**-$2,548.8**	**-$6,187.2**	**-$13,029.4**
Alabama	-$11.0	-$35.5	-$82.0	-$198.3
Arizona	-$25.7	-$171.4	-$457.9	-$632.9
Arkansas	-$4.9	-$20.8	-$41.6	-$102.8
California	-$25.7	-$118.7	-$400.3	-$449.3
Colorado	-$4.9	-$110.2	-$138.3	-$271.8
Connecticut	-$6.1	-$24.5	-$56.3	-$113.9
Delaware	-$2.4	-$7.3	-$15.9	-$33.1
District of Columbia	-$1.2	-$4.9	-$12.2	-$29.4
Florida	-$79.6	-$189.8	-$396.6	-$750.4
Georgia	-$44.1	-$104.1	-$216.7	-$457.9
Idaho	$1.2	$0.0	-$1.2	-$2.4
Illinois	$4.9	-$12.2	-$97.9	-$461.5
Indiana	-$1.2	-$44.1	-$184.9	-$510.5
Iowa	$2.4	-$7.3	-$30.6	-$100.4
Kansas	-$3.7	-$18.4	-$35.5	-$111.4
Kentucky	-$7.3	-$35.5	-$225.3	-$602.3
Louisiana	-$7.3	-$29.4	-$61.2	-$149.4
Maine	-$1.2	-$4.9	-$12.2	-$22.0
Maryland	-$13.5	-$46.5	-$102.8	-$222.8
Massachusetts	-$7.3	-$36.7	-$84.5	-$176.3
Michigan	-$4.9	-$33.1	-$139.6	-$352.6
Minnesota	-$1.2	-$24.5	-$85.7	-$249.7
Mississippi	-$2.4	-$12.2	-$31.8	-$77.1
Missouri	-$1.2	-$14.7	-$46.5	-$184.9
Montana	$0.0	-$1.2	-$6.1	-$13.5
Nebraska	-$2.4	-$11.0	-$30.6	-$68.6
Nevada	-$4.9	-$44.1	-$210.6	-$183.6
New Hampshire	-$1.2	-$7.3	-$18.4	-$39.2
New Jersey	-$23.3	-$75.9	-$162.8	-$329.3
New Mexico	-$9.8	-$115.1	-$151.8	-$277.9
New York	-$44.1	-$155.5	-$363.6	-$749.2
North Carolina	-$29.4	-$77.1	-$173.8	-$373.4
North Dakota	$0.0	-$3.7	-$9.8	-$22.0
Ohio	-$6.1	-$96.7	-$308.5	-$714.9
Oklahoma	-$14.7	-$183.6	-$113.9	-$361.1
Oregon	$8.6	$12.2	$33.1	$58.8
Pennsylvania	-$33.1	-$123.6	-$292.6	-$618.2
Rhode Island	-$1.2	-$4.9	-$11.0	-$20.8
South Carolina	-$11.0	-$28.2	-$61.2	-$134.7
South Dakota	$0.0	-$3.7	-$8.6	-$22.0
Tennessee	-$23.3	-$82.0	-$263.2	-$549.7
Texas	-$62.4	-$225.3	-$406.4	-$864.3
Utah	-$7.3	-$34.3	-$138.3	-$177.5
Vermont	-$1.2	-$3.7	-$12.2	-$25.7
Virginia	-$18.4	-$66.1	-$150.6	-$322.0
Washington	$8.6	$11.0	$34.3	$51.4
West Virginia	-$2.4	-$100.4	-$312.2	-$700.3
Wisconsin	-$1.2	-$14.7	-$68.6	-$224.0
Wyoming	-$1.2	-$7.3	-$15.9	-$68.6

Table E-14. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Information ($M)

Region	2020	2030	2040	2050
United States	**-$544.8**	**-$2,152.2**	**-$4,409.6**	**-$7,957.4**
Alabama	-$6.1	-$18.4	-$39.2	-$80.8
Arizona	-$17.1	-$88.1	-$194.7	-$253.4
Arkansas	-$2.4	-$9.8	-$20.8	-$42.8
California	-$68.6	-$328.1	-$793.3	-$1,005.1
Colorado	-$17.1	-$132.2	-$180.0	-$311.0
Connecticut	-$4.9	-$18.4	-$36.7	-$71.0
Delaware	-$1.2	-$3.7	-$7.3	-$13.5
District of Columbia	-$4.9	-$18.4	-$35.5	-$69.8
Florida	-$66.1	-$142.0	-$248.5	-$417.5
Georgia	-$53.9	-$131.0	-$251.0	-$466.4
Idaho	$0.0	-$2.4	-$3.7	-$4.9
Illinois	$2.4	-$14.7	-$80.8	-$271.8
Indiana	-$1.2	-$13.5	-$51.4	-$129.8
Iowa	$1.2	-$6.1	-$22.0	-$57.5
Kansas	-$4.9	-$26.9	-$50.2	-$111.4
Kentucky	-$3.7	-$13.5	-$53.9	-$128.5
Louisiana	-$3.7	-$12.2	-$24.5	-$51.4
Maine	$0.0	-$2.4	-$4.9	-$11.0
Maryland	-$9.8	-$34.3	-$68.6	-$134.7
Massachusetts	-$9.8	-$39.2	-$80.8	-$175.1
Michigan	-$2.4	-$17.1	-$58.8	-$140.8
Minnesota	$1.2	-$12.2	-$40.4	-$110.2
Mississippi	-$1.2	-$6.1	-$12.2	-$25.7
Missouri	-$3.7	-$20.8	-$51.4	-$131.0
Montana	$0.0	-$2.4	-$4.9	-$9.8
Nebraska	$1.2	-$7.3	-$15.9	-$35.5
Nevada	-$3.7	-$20.8	-$67.3	-$56.3
New Hampshire	-$1.2	-$4.9	-$9.8	-$22.0
New Jersey	-$22.0	-$72.2	-$140.8	-$265.7
New Mexico	-$4.9	-$38.0	-$49.0	-$80.8
New York	-$58.8	-$195.9	-$404.0	-$771.3
North Carolina	-$20.8	-$53.9	-$104.1	-$202.0
North Dakota	$0.0	-$2.4	-$6.1	-$13.5
Ohio	-$3.7	-$41.6	-$120.0	-$268.1
Oklahoma	-$12.2	-$64.9	-$53.9	-$120.0
Oregon	$3.7	$2.4	$8.6	$24.5
Pennsylvania	-$19.6	-$66.1	-$134.7	-$260.8
Rhode Island	-$1.2	-$3.7	-$7.3	-$14.7
South Carolina	-$6.1	-$17.1	-$34.3	-$67.3
South Dakota	$0.0	-$2.4	-$4.9	-$11.0
Tennessee	-$11.0	-$36.7	-$94.3	-$192.2
Texas	-$62.4	-$214.2	-$334.2	-$624.4
Utah	-$7.3	-$31.8	-$84.5	-$111.4
Vermont	$0.0	-$2.4	-$4.9	-$9.8
Virginia	-$25.7	-$85.7	-$171.4	-$323.2
Washington	-$9.8	-$52.6	-$82.0	-$112.6
West Virginia	-$1.2	-$15.9	-$41.6	-$90.6
Wisconsin	$0.0	-$7.3	-$29.4	-$83.2
Wyoming	$0.0	-$2.4	-$6.1	-$14.7

Table E-15. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Management of Companies and Enterprises ($M)

Region	2020	2030	2040	2050
United States	**-$231.4**	**-$744.3**	**-$1,033.2**	**-$1,051.6**
Alabama	-$3.7	-$6.1	-$7.3	-$8.6
Arizona	-$4.9	-$34.3	-$56.3	-$44.1
Arkansas	-$3.7	-$13.5	-$12.2	-$14.7
California	-$14.7	-$51.4	-$89.4	-$19.6
Colorado	$0.0	-$28.2	-$24.5	-$25.7
Connecticut	-$3.7	-$11.0	-$13.5	-$13.5
Delaware	-$2.4	-$4.9	-$6.1	-$6.1
District of Columbia	$0.0	-$1.2	-$1.2	-$1.2
Florida	-$31.8	-$47.7	-$52.6	-$50.2
Georgia	-$28.2	-$41.6	-$46.5	-$46.5
Idaho	$1.2	$0.0	-$1.2	$0.0
Illinois	$2.4	-$6.1	-$24.5	-$50.2
Indiana	$0.0	-$6.1	-$14.7	-$20.8
Iowa	$0.0	$0.0	-$2.4	-$3.7
Kansas	$0.0	-$2.4	-$2.4	-$3.7
Kentucky	-$3.7	-$7.3	-$24.5	-$31.8
Louisiana	-$1.2	-$4.9	-$6.1	-$8.6
Maine	$0.0	$0.0	$0.0	$0.0
Maryland	-$2.4	-$7.3	-$8.6	-$9.8
Massachusetts	-$1.2	-$8.6	-$11.0	-$14.7
Michigan	-$1.2	-$11.0	-$24.5	-$30.6
Minnesota	-$2.4	-$15.9	-$24.5	-$38.0
Mississippi	-$1.2	-$2.4	-$2.4	-$3.7
Missouri	-$2.4	-$14.7	-$20.8	-$31.8
Montana	$0.0	$0.0	$0.0	$0.0
Nebraska	-$1.2	-$3.7	-$4.9	-$6.1
Nevada	-$1.2	-$22.0	-$64.9	-$30.6
New Hampshire	$0.0	-$2.4	-$2.4	-$3.7
New Jersey	-$12.2	-$31.8	-$36.7	-$38.0
New Mexico	-$1.2	-$13.5	-$11.0	-$11.0
New York	-$29.4	-$72.2	-$88.1	-$93.0
North Carolina	-$22.0	-$39.2	-$47.7	-$52.6
North Dakota	$0.0	-$1.2	-$1.2	-$1.2
Ohio	-$4.9	-$38.0	-$68.6	-$84.5
Oklahoma	-$3.7	-$29.4	-$12.2	-$18.4
Oregon	$6.1	$6.1	$11.0	$13.5
Pennsylvania	-$19.6	-$52.6	-$67.3	-$72.2
Rhode Island	$0.0	-$2.4	-$2.4	-$2.4
South Carolina	-$3.7	-$6.1	-$7.3	-$7.3
South Dakota	$0.0	$0.0	-$1.2	-$1.2
Tennessee	-$6.1	-$12.2	-$19.6	-$20.8
Texas	-$13.5	-$35.5	-$39.2	-$46.5
Utah	-$1.2	-$9.8	-$23.3	-$15.9
Vermont	$0.0	$0.0	$0.0	$0.0
Virginia	-$18.4	-$45.3	-$56.3	-$61.2
Washington	$6.1	$7.3	$14.7	$17.1
West Virginia	$0.0	-$9.8	-$18.4	-$22.0
Wisconsin	$0.0	-$2.4	-$8.6	-$14.7
Wyoming	$0.0	-$1.2	-$1.2	-$2.4

Table E-16. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Manufacturing ($M)

Region	2020	2030	2040	2050
United States	**-$1,878.0**	**-$5,584.9**	**-$11,571.3**	**-$20,786.0**
Alabama	-$73.5	-$178.7	-$385.6	-$916.9
Arizona	-$47.7	-$199.5	-$385.6	-$548.5
Arkansas	-$30.6	-$63.7	-$180.0	-$488.5
California	-$167.7	-$771.3	-$1,854.7	-$379.5
Colorado	$28.2	-$6.1	$45.3	$79.6
Connecticut	$7.3	$4.9	$8.6	$18.4
Delaware	-$8.6	-$22.0	-$36.7	-$72.2
District of Columbia	$0.0	$0.0	$0.0	$0.0
Florida	-$286.5	-$549.7	-$937.8	-$1,662.5
Georgia	-$306.1	-$592.5	-$1,068.7	-$2,206.0
Idaho	$11.0	$18.4	$62.4	$132.2
Illinois	$68.6	$140.8	-$31.8	-$422.4
Indiana	$12.2	-$34.3	-$277.9	-$630.5
Iowa	$15.9	$45.3	-$33.1	-$140.8
Kansas	-$9.8	-$30.6	-$80.8	-$159.1
Kentucky	-$67.3	-$160.4	-$391.8	-$913.3
Louisiana	-$17.1	-$61.2	-$109.0	-$285.2
Maine	$6.1	$11.0	$18.4	$36.7
Maryland	-$23.3	-$58.8	-$101.6	-$216.7
Massachusetts	$22.0	$29.4	$68.6	$120.0
Michigan	-$2.4	-$63.7	-$290.1	-$700.3
Minnesota	$6.1	$9.8	-$68.6	-$231.4
Mississippi	-$4.9	-$26.9	-$71.0	-$215.5
Missouri	$31.8	$49.0	$11.0	-$74.7

Region	2020	2030	2040	2050
Montana	$6.1	$9.8	$23.3	$45.3
Nebraska	-$4.9	-$3.7	-$36.7	-$85.7
Nevada	-$2.4	-$15.9	-$56.3	-$35.5
New Hampshire	$3.7	$2.4	$3.7	$1.2
New Jersey	-$40.4	-$120.0	-$204.4	-$401.5
New Mexico	-$8.6	-$52.6	-$77.1	-$116.3
New York	-$126.1	-$303.6	-$544.8	-$974.5
North Carolina	-$219.1	-$446.8	-$784.7	-$1,557.2
North Dakota	-$1.2	-$2.4	-$8.6	-$19.6
Ohio	$30.6	-$96.7	-$302.4	-$717.4
Oklahoma	-$58.8	-$176.3	-$299.9	-$614.6
Oregon	$53.9	$86.9	$232.6	$446.8
Pennsylvania	-$155.5	-$417.5	-$739.4	-$1,385.8
Rhode Island	$1.2	$2.4	$6.1	$14.7
South Carolina	-$69.8	-$146.9	-$262.0	-$554.6
South Dakota	$0.0	-$2.4	-$8.6	-$26.9
Tennessee	-$129.8	-$323.2	-$689.2	-$1,433.6
Texas	-$284.0	-$893.7	-$1,393.2	-$2,725.1
Utah	-$13.5	-$63.7	-$154.3	-$228.9
Vermont	$3.7	$4.9	$3.7	$8.6
Virginia	-$110.2	-$243.6	-$390.5	-$756.6
Washington	$75.9	$131.0	$369.7	$673.3
West Virginia	-$9.8	-$44.1	-$100.4	-$183.6
Wisconsin	$7.3	$20.8	-$107.7	-$358.7
Wyoming	$0.0	-$2.4	-$3.7	-$9.8

Table E-17. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Mining ($M)

Region	2020	2030	2040	2050	Region	2020	2030	2040	2050
United States	**-$126.1**	**-$5,106.2**	**-$11,485.6**	**-$19,774.8**	Montana	-$1.2	-$11.0	-$35.5	-$58.8
Alabama	-$1.2	-$11.0	-$33.1	-$66.1	Nebraska	-$2.4	-$3.7	-$13.5	-$25.7
Arizona	-$3.7	-$606.0	-$1,436.0	-$1,265.8	Nevada	-$3.7	-$326.9	-$1,722.5	-$1,063.8
Arkansas	-$1.2	-$4.9	-$13.5	-$39.2	New Hampshire	$0.0	$0.0	-$1.2	-$3.7
California	$1.2	-$20.8	-$55.1	-$78.4	New Jersey	$0.0	-$1.2	-$4.9	-$8.6
Colorado	-$4.9	-$362.4	-$421.1	-$648.8	New Mexico	-$30.6	-$572.9	-$547.2	-$707.6
Connecticut	$0.0	-$1.2	-$2.4	-$4.9	New York	$0.0	-$3.7	-$12.2	-$23.3
Delaware	$0.0	$0.0	$0.0	$0.0	North Carolina	-$1.2	-$6.1	-$19.6	-$39.2
District of Columbia	$0.0	$0.0	$0.0	-$1.2	North Dakota	-$1.2	-$6.1	-$15.9	-$31.8
Florida	-$1.2	-$3.7	-$12.2	-$23.3	Ohio	-$1.2	-$157.9	-$471.3	-$859.4
Georgia	-$1.2	-$9.8	-$30.6	-$58.8	Oklahoma	-$6.1	-$1,068.7	-$260.8	-$929.2
Idaho	$0.0	-$3.7	-$12.2	-$18.4	Oregon	$0.0	-$2.4	-$7.3	-$9.8
Illinois	-$1.2	-$11.0	-$66.1	-$880.2	Pennsylvania	-$2.4	-$26.9	-$82.0	-$161.6
Indiana	-$1.2	-$148.1	-$494.6	-$1,145.9	Rhode Island	$0.0	$0.0	-$1.2	-$1.2
Iowa	$0.0	-$23.3	-$40.4	-$194.7	South Carolina	$0.0	-$1.2	-$4.9	-$9.8
Kansas	-$1.2	-$11.0	-$31.8	-$140.8	South Dakota	$0.0	-$1.2	-$2.4	-$6.1
Kentucky	-$4.9	-$38.0	-$1,056.5	-$2,453.3	Tennessee	$0.0	-$35.5	-$280.3	-$394.2
Louisiana	-$7.3	-$42.8	-$97.9	-$217.9	Texas	-$28.2	-$216.7	-$346.5	-$726.0
Maine	$0.0	$0.0	$0.0	$0.0	Utah	-$2.4	-$57.5	-$399.1	-$331.8
Maryland	$0.0	-$2.4	-$6.1	-$12.2	Vermont	$0.0	-$8.6	-$34.3	-$56.3
Massachusetts	$0.0	-$1.2	-$3.7	-$7.3	Virginia	-$1.2	-$13.5	-$41.6	-$83.2
Michigan	-$1.2	-$7.3	-$151.8	-$331.8	Washington	$0.0	-$4.9	-$15.9	-$23.3
Minnesota	-$1.2	-$7.3	-$95.5	-$395.4	West Virginia	-$4.9	-$1,193.6	-$2,880.6	-$5,167.4
Mississippi	-$1.2	-$4.9	-$12.2	-$25.7	Wisconsin	$0.0	-$3.7	-$42.8	-$221.6
Missouri	-$1.2	-$7.3	-$23.3	-$293.8	Wyoming	-$4.9	-$39.2	-$107.7	-$455.4

Table E-18. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Other Services, except Public Administration ($M)

Region	2020	2030	2040	2050
United States	**-$178.7**	**-$711.3**	**-$1,500.9**	**-$2,771.6**
Alabama	-$4.9	-$11.0	-$22.0	-$45.3
Arizona	-$8.6	-$41.6	-$91.8	-$110.2
Arkansas	-$1.2	-$4.9	-$8.6	-$19.6
California	-$9.8	-$44.1	-$129.8	-$120.0
Colorado	-$2.4	-$31.8	-$34.3	-$60.0
Connecticut	-$1.2	-$6.1	-$12.2	-$23.3
Delaware	-$1.2	-$2.4	-$3.7	-$7.3
District of Columbia	-$1.2	-$4.9	-$9.8	-$18.4
Florida	-$29.4	-$58.8	-$101.6	-$171.4
Georgia	-$18.4	-$35.5	-$61.2	-$111.4
Idaho	$0.0	$0.0	$0.0	$1.2
Illinois	$2.4	-$3.7	-$31.8	-$116.3
Indiana	$0.0	-$11.0	-$42.8	-$102.8
Iowa	$2.4	$0.0	-$7.3	-$22.0
Kansas	-$1.2	-$4.9	-$8.6	-$22.0
Kentucky	-$2.4	-$8.6	-$46.5	-$110.2
Louisiana	-$2.4	-$8.6	-$15.9	-$36.7
Maine	$0.0	$0.0	-$1.2	-$2.4
Maryland	-$4.9	-$15.9	-$31.8	-$60.0
Massachusetts	-$1.2	-$7.3	-$17.1	-$36.7
Michigan	-$1.2	-$8.6	-$31.8	-$71.0
Minnesota	$1.2	-$4.9	-$17.1	-$46.5
Mississippi	-$1.2	-$2.4	-$7.3	-$15.9
Missouri	$0.0	-$4.9	-$14.7	-$46.5
Montana	$0.0	$0.0	-$1.2	-$2.4
Nebraska	$1.2	-$2.4	-$6.1	-$13.5
Nevada	-$2.4	-$13.5	-$51.4	-$38.0
New Hampshire	$0.0	-$1.2	-$3.7	-$7.3
New Jersey	-$7.3	-$19.6	-$38.0	-$68.6
New Mexico	-$3.7	-$26.9	-$29.4	-$46.5
New York	-$13.5	-$41.6	-$86.9	-$157.9
North Carolina	-$9.8	-$20.8	-$39.2	-$75.9
North Dakota	$0.0	-$1.2	-$2.4	-$4.9
Ohio	-$1.2	-$25.7	-$74.7	-$156.7
Oklahoma	-$6.1	-$46.5	-$25.7	-$72.2
Oregon	$3.7	$4.9	$9.8	$14.7
Pennsylvania	-$9.8	-$29.4	-$58.8	-$111.4
Rhode Island	$0.0	-$1.2	-$2.4	-$3.7
South Carolina	-$4.9	-$9.8	-$18.4	-$35.5
South Dakota	$1.2	$0.0	-$1.2	-$3.7
Tennessee	-$7.3	-$22.0	-$60.0	-$112.6
Texas	-$23.3	-$69.8	-$106.5	-$200.8
Utah	-$2.4	-$12.2	-$35.5	-$40.4
Vermont	$0.0	$0.0	-$1.2	-$3.7
Virginia	-$8.6	-$25.7	-$49.0	-$91.8
Washington	$3.7	$4.9	$12.2	$17.1
West Virginia	-$1.2	-$24.5	-$63.7	-$123.6
Wisconsin	$0.0	-$2.4	-$13.5	-$39.2
Wyoming	$0.0	-$2.4	-$4.9	-$15.9

Table E-19. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Professional and Technical Services ($M)

Region	2020	2030	2040	2050
United States	**-$581.5**	**-$2,062.8**	**-$3,187.9**	**-$4,421.9**
Alabama	-$11.0	-$24.5	-$36.7	-$57.5
Arizona	-$24.5	-$106.5	-$178.7	-$175.1
Arkansas	-$2.4	-$6.1	-$8.6	-$14.7
California	-$45.3	-$206.9	-$382.0	-$254.6
Colorado	-$12.2	-$106.5	-$91.8	-$124.9
Connecticut	-$4.9	-$18.4	-$28.2	-$42.8
Delaware	-$2.4	-$7.3	-$11.0	-$17.1
District of Columbia	-$12.2	-$39.2	-$62.4	-$97.9
Florida	-$88.1	-$150.6	-$195.9	-$255.9
Georgia	-$50.2	-$86.9	-$117.5	-$164.0
Idaho	$0.0	-$2.4	-$2.4	-$2.4
Illinois	$9.8	-$18.4	-$91.8	-$235.1
Indiana	$0.0	-$12.2	-$38.0	-$69.8
Iowa	$4.9	$1.2	-$4.9	-$13.5
Kansas	-$1.2	-$8.6	-$11.0	-$22.0
Kentucky	-$3.7	-$12.2	-$46.5	-$83.2
Louisiana	-$3.7	-$13.5	-$17.1	-$28.2
Maine	$0.0	-$1.2	-$2.4	-$3.7
Maryland	-$20.8	-$63.7	-$99.2	-$155.5
Massachusetts	-$11.0	-$46.5	-$73.5	-$122.4
Michigan	-$3.7	-$31.8	-$82.0	-$145.7
Minnesota	$7.3	-$4.9	-$25.7	-$60.0
Mississippi	-$1.2	-$3.7	-$6.1	-$11.0
Missouri	$0.0	-$8.6	-$19.6	-$49.0
Montana	$0.0	-$1.2	-$1.2	-$2.4
Nebraska	$4.9	-$2.4	-$6.1	-$11.0
Nevada	-$8.6	-$40.4	-$102.8	-$61.2
New Hampshire	-$1.2	-$3.7	-$6.1	-$11.0
New Jersey	-$26.9	-$79.6	-$121.2	-$180.0
New Mexico	-$12.2	-$77.1	-$67.3	-$78.4
New York	-$60.0	-$182.4	-$299.9	-$446.8
North Carolina	-$23.3	-$45.3	-$64.9	-$95.5
North Dakota	$1.2	-$1.2	-$1.2	-$2.4
Ohio	-$1.2	-$45.3	-$99.2	-$164.0
Oklahoma	-$14.7	-$88.1	-$38.0	-$68.6
Oregon	$6.1	$7.3	$14.7	$19.6
Pennsylvania	-$31.8	-$89.4	-$135.9	-$199.5
Rhode Island	$0.0	-$2.4	-$3.7	-$4.9
South Carolina	-$8.6	-$15.9	-$22.0	-$33.1
South Dakota	$1.2	$0.0	-$1.2	-$1.2
Tennessee	-$14.7	-$38.0	-$72.2	-$105.3
Texas	-$74.7	-$199.5	-$225.3	-$328.1
Utah	-$7.3	-$26.9	-$58.8	-$55.1
Vermont	$0.0	-$2.4	-$3.7	-$6.1
Virginia	-$40.4	-$121.2	-$186.1	-$282.8
Washington	$8.6	$7.3	$22.0	$29.4
West Virginia	-$1.2	-$29.4	-$53.9	-$79.6
Wisconsin	$1.2	-$2.4	-$14.7	-$35.5
Wyoming	-$1.2	-$3.7	-$4.9	-$11.0

Table E-20. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Real Estate and Rental and Leasing ($M)

Region	2020	2030	2040	2050
United States	**-$530.1**	**-$2,504.8**	**-$3,886.9**	**-$6,048.9**
Alabama	-$12.2	-$25.7	-$40.4	-$78.4
Arizona	-$62.4	-$266.9	-$441.9	-$422.4
Arkansas	-$3.7	-$12.2	-$15.9	-$31.8
California	$31.8	-$61.2	-$156.7	$400.3
Colorado	-$12.2	-$170.2	-$115.1	-$157.9
Connecticut	$0.0	-$7.3	-$13.5	-$28.2
Delaware	-$2.4	-$6.1	-$9.8	-$19.6
District of Columbia	-$6.1	-$22.0	-$47.7	-$97.9
Florida	-$153.0	-$303.6	-$448.1	-$751.7
Georgia	-$75.9	-$144.5	-$231.4	-$411.3
Idaho	$2.4	$2.4	$4.9	$12.2
Illinois	$29.4	$23.3	-$77.1	-$366.0
Indiana	$4.9	-$18.4	-$82.0	-$187.3
Iowa	$4.9	$2.4	-$7.3	-$26.9
Kansas	-$1.2	-$9.8	-$9.8	-$30.6
Kentucky	-$4.9	-$17.1	-$85.7	-$166.5
Louisiana	-$6.1	-$26.9	-$24.5	-$46.5
Maine	$1.2	$1.2	$1.2	$0.0
Maryland	-$15.9	-$61.2	-$117.5	-$243.6
Massachusetts	$7.3	$4.9	$1.2	-$19.6
Michigan	$6.1	$1.2	-$40.4	-$111.4
Minnesota	$11.0	$7.3	-$20.8	-$86.9
Mississippi	-$1.2	-$6.1	-$9.8	-$20.8
Missouri	$3.7	-$2.4	-$14.7	-$73.5

Region	2020	2030	2040	2050
Montana	$1.2	$0.0	-$1.2	-$1.2
Nebraska	$1.2	-$2.4	-$7.3	-$15.9
Nevada	-$18.4	-$93.0	-$247.3	-$124.9
New Hampshire	$1.2	$0.0	$0.0	-$3.7
New Jersey	-$12.2	-$44.1	-$80.8	-$151.8
New Mexico	-$15.9	-$112.6	-$79.6	-$96.7
New York	-$19.6	-$120.0	-$279.1	-$565.6
North Carolina	-$39.2	-$77.1	-$122.4	-$224.0
North Dakota	$0.0	-$1.2	-$2.4	-$3.7
Ohio	$6.1	-$55.1	-$145.7	-$301.2
Oklahoma	-$19.6	-$286.5	-$63.7	-$154.3
Oregon	$18.4	$29.4	$57.5	$99.2
Pennsylvania	-$22.0	-$63.7	-$107.7	-$194.7
Rhode Island	$1.2	$1.2	$1.2	-$1.2
South Carolina	-$19.6	-$39.2	-$61.2	-$115.1
South Dakota	$1.2	$0.0	-$1.2	-$3.7
Tennessee	-$24.5	-$64.9	-$139.6	-$230.2
Texas	-$116.3	-$333.0	-$359.9	-$615.8
Utah	-$11.0	-$44.1	-$100.4	-$90.6
Vermont	$0.0	-$1.2	-$2.4	-$4.9
Virginia	-$26.9	-$83.2	-$145.7	-$284.0
Washington	$30.6	$50.2	$104.1	$178.7
West Virginia	-$1.2	-$57.5	-$101.6	-$132.2
Wisconsin	$4.9	$7.3	-$8.6	-$47.7
Wyoming	-$1.2	-$7.3	-$7.3	-$24.5

Table E-21. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Retail Trade ($M)

Region	2020	2030	2040	2050
United States	**-$1,223.0**	**-$3,879.6**	**-$8,744.6**	**-$17,330.1**
Alabama	-$25.7	-$61.2	-$133.4	-$314.6
Arizona	-$56.3	-$279.1	-$690.5	-$945.1
Arkansas	-$9.8	-$25.7	-$53.9	-$134.7
California	-$64.9	-$198.3	-$797.0	-$244.8
Colorado	-$12.2	-$132.2	-$150.6	-$292.6
Connecticut	-$12.2	-$30.6	-$57.5	-$112.6
Delaware	-$4.9	-$12.2	-$23.3	-$47.7
District of Columbia	-$1.2	-$2.4	-$6.1	-$13.5
Florida	-$184.9	-$390.5	-$760.2	-$1,376.0
Georgia	-$96.7	-$203.2	-$407.7	-$830.0
Idaho	$1.2	$0.0	$4.9	$20.8
Illinois	$0.0	-$8.6	-$111.4	-$591.3
Indiana	-$6.1	-$50.2	-$222.8	-$653.7
Iowa	-$3.7	-$11.0	-$44.1	-$146.9
Kansas	-$9.8	-$25.7	-$47.7	-$139.6
Kentucky	-$15.9	-$52.6	-$282.8	-$814.1
Louisiana	-$15.9	-$45.3	-$86.9	-$210.6
Maine	-$2.4	-$7.3	-$14.7	-$28.2
Maryland	-$28.2	-$69.8	-$133.4	-$290.1
Massachusetts	-$11.0	-$29.4	-$55.1	-$122.4
Michigan	-$12.2	-$38.0	-$162.8	-$453.0
Minnesota	-$7.3	-$14.7	-$67.3	-$221.6
Mississippi	-$8.6	-$22.0	-$52.6	-$126.1
Missouri	-$7.3	-$22.0	-$61.2	-$236.3

Region	2020	2030	2040	2050
Montana	$0.0	-$2.4	-$6.1	-$14.7
Nebraska	-$8.6	-$15.9	-$36.7	-$82.0
Nevada	-$20.8	-$104.1	-$363.6	-$313.4
New Hampshire	-$3.7	-$9.8	-$20.8	-$46.5
New Jersey	-$47.7	-$110.2	-$204.4	-$406.4
New Mexico	-$22.0	-$160.4	-$208.1	-$370.9
New York	-$88.1	-$213.0	-$427.3	-$852.1
North Carolina	-$62.4	-$134.7	-$273.0	-$577.8
North Dakota	-$2.4	-$6.1	-$13.5	-$30.6
Ohio	-$14.7	-$106.5	-$335.4	-$845.9
Oklahoma	-$41.6	-$235.1	-$176.3	-$487.2
Oregon	$14.7	$28.2	$78.4	$170.2
Pennsylvania	-$62.4	-$153.0	-$307.3	-$652.5
Rhode Island	-$1.2	-$3.7	-$6.1	-$12.2
South Carolina	-$30.6	-$67.3	-$139.6	-$291.4
South Dakota	-$2.4	-$4.9	-$11.0	-$28.2
Tennessee	-$44.1	-$131.0	-$368.5	-$795.7
Texas	-$132.2	-$401.5	-$652.5	-$1,365.0
Utah	-$15.9	-$68.6	-$222.8	-$299.9
Vermont	-$2.4	-$6.1	-$14.7	-$31.8
Virginia	-$44.1	-$113.9	-$227.7	-$489.7
Washington	$20.8	$38.0	$126.1	$242.4
West Virginia	-$6.1	-$140.8	-$424.8	-$1,067.5
Wisconsin	-$4.9	-$9.8	-$62.4	-$227.7
Wyoming	-$4.9	-$18.4	-$33.1	-$134.7

Table E-22. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Transportation and Warehousing ($M)

Region	2020	2030	2040	2050	Region	2020	2030	2040	2050
United States	**-$309.7**	**-$1,248.7**	**-$2,536.6**	**-$4,004.4**	Montana	$0.0	-$3.7	-$9.8	-$12.2
Alabama	-$6.1	-$19.6	-$36.7	-$64.9	Nebraska	-$2.4	-$17.1	-$39.2	-$67.3
Arizona	-$9.8	-$66.1	-$143.2	-$149.4	Nevada	-$2.4	-$19.6	-$69.8	-$47.7
Arkansas	-$4.9	-$19.6	-$36.7	-$64.9	New Hampshire	$0.0	-$1.2	-$2.4	-$4.9
California	-$15.9	-$74.7	-$177.5	-$105.3	New Jersey	-$13.5	-$36.7	-$64.9	-$104.1
Colorado	-$2.4	-$36.7	-$49.0	-$73.5	New Mexico	-$2.4	-$20.8	-$30.6	-$41.6
Connecticut	-$1.2	-$6.1	-$11.0	-$18.4	New York	-$15.9	-$51.4	-$94.3	-$154.3
Delaware	-$1.2	-$2.4	-$4.9	-$7.3	North Carolina	-$14.7	-$39.2	-$72.2	-$121.2
District of Columbia	$0.0	-$1.2	-$2.4	-$4.9	North Dakota	$0.0	-$2.4	-$7.3	-$12.2
Florida	-$34.3	-$72.2	-$118.7	-$178.7	Ohio	-$8.6	-$52.6	-$128.5	-$236.3
Georgia	-$31.8	-$72.2	-$123.6	-$197.1	Oklahoma	-$4.9	-$34.3	-$35.5	-$67.3
Idaho	$0.0	-$3.7	-$8.6	-$8.6	Oregon	$3.7	$0.0	$1.2	$7.3
Illinois	-$2.4	-$30.6	-$93.0	-$225.3	Pennsylvania	-$18.4	-$57.5	-$110.2	-$182.4
Indiana	-$4.9	-$28.2	-$77.1	-$153.0	Rhode Island	$0.0	-$1.2	-$2.4	-$3.7
Iowa	-$1.2	-$11.0	-$28.2	-$55.1	South Carolina	-$6.1	-$15.9	-$29.4	-$50.2
Kansas	-$2.4	-$13.5	-$25.7	-$47.7	South Dakota	$0.0	-$2.4	-$6.1	-$9.8
Kentucky	-$7.3	-$31.8	-$96.7	-$187.3	Tennessee	-$19.6	-$61.2	-$134.7	-$231.4
Louisiana	-$3.7	-$14.7	-$26.9	-$46.5	Texas	-$42.8	-$145.7	-$226.5	-$352.6
Maine	$0.0	-$2.4	-$3.7	-$7.3	Utah	-$3.7	-$19.6	-$57.5	-$61.2
Maryland	-$4.9	-$15.9	-$30.6	-$51.4	Vermont	$0.0	-$1.2	-$2.4	-$4.9
Massachusetts	-$1.2	-$7.3	-$14.7	-$25.7	Virginia	-$9.8	-$31.8	-$60.0	-$101.6
Michigan	-$3.7	-$19.6	-$52.6	-$100.4	Washington	$4.9	$2.4	$7.3	$15.9
Minnesota	-$1.2	-$12.2	-$33.1	-$69.8	West Virginia	-$1.2	-$15.9	-$39.2	-$71.0
Mississippi	-$3.7	-$11.0	-$20.8	-$36.7	Wisconsin	-$2.4	-$15.9	-$41.6	-$86.9
Missouri	-$3.7	-$20.8	-$45.3	-$94.3	Wyoming	-$1.2	-$6.1	-$12.2	-$20.8

Table E-23. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Utilities ($M)

Region	2020	2030	2040	2050	Region	2020	2030	2040	2050
United States	**$128.5**	**$871.6**	**$1,557.2**	**$270.6**	Montana	$2.4	$3.7	$6.1	$6.1
Alabama	-$1.2	-$17.1	$149.4	$93.0	Nebraska	-$11.0	-$14.7	-$15.9	-$18.4
Arizona	-$91.8	$64.9	$154.3	$31.8	Nevada	-$20.8	-$18.4	-$9.8	-$26.9
Arkansas	-$7.3	-$8.6	-$17.1	-$7.3	New Hampshire	$0.0	$15.9	$18.4	$20.8
California	$255.9	$497.0	$1,590.3	$752.9	New Jersey	-$1.2	$15.9	$41.6	$51.4
Colorado	-$23.3	-$14.7	-$2.4	-$4.9	New Mexico	-$29.4	-$49.0	-$51.4	-$57.5
Connecticut	$18.4	$26.9	$28.2	$26.9	New York	-$3.7	$64.9	$85.7	$73.5
Delaware	$2.4	$3.7	$4.9	$6.1	North Carolina	$30.6	$90.6	$132.2	$122.4
District of Columbia	$0.0	$0.0	$0.0	$0.0	North Dakota	-$7.3	-$9.8	-$8.6	-$15.9
Florida	-$17.1	$4.9	$33.1	$226.5	Ohio	$3.7	-$82.0	-$161.6	-$252.2
Georgia	$18.4	$14.7	$109.0	$120.0	Oklahoma	-$51.4	-$38.0	-$89.4	-$45.3
Idaho	$1.2	$2.4	$3.7	$4.9	Oregon	$4.9	$8.6	$13.5	$19.6
Illinois	$8.6	$9.8	-$106.5	-$254.6	Pennsylvania	-$2.4	$146.9	$181.2	$143.2
Indiana	$2.4	-$49.0	-$153.0	-$241.2	Rhode Island	$4.9	$2.4	$6.1	$6.1
Iowa	$2.4	-$4.9	-$40.4	-$73.5	South Carolina	$42.8	$61.2	$124.9	$148.1
Kansas	-$24.5	-$30.6	-$38.0	-$44.1	South Dakota	$2.4	$2.4	$2.4	$2.4
Kentucky	$0.0	-$23.3	-$91.8	-$230.2	Tennessee	-$28.2	-$97.9	-$146.9	-$182.4
Louisiana	$0.0	-$3.7	-$1.2	$77.1	Texas	-$15.9	$345.2	$111.4	$410.1
Maine	$0.0	$1.2	$6.1	$9.8	Utah	-$20.8	-$34.3	-$39.2	-$50.2
Maryland	$0.0	-$1.2	$14.7	$25.7	Vermont	$0.0	-$1.2	-$4.9	-$4.9
Massachusetts	$23.3	$33.1	$38.0	$46.5	Virginia	$51.4	$60.0	$66.1	$63.7
Michigan	$3.7	-$3.7	-$74.7	-$170.2	Washington	$4.9	$8.6	$13.5	$18.4
Minnesota	$7.3	$1.2	-$26.9	-$60.0	West Virginia	$0.0	-$101.6	-$213.0	-$324.4
Mississippi	$1.2	$2.4	$8.6	$4.9	Wisconsin	$2.4	-$1.2	-$29.4	-$79.6
Missouri	$4.9	$7.3	-$41.6	-$69.8	Wyoming	-$15.9	-$23.3	-$26.9	-$31.8

Table E-24. Change in Contribution to GDP and GSP by State and Industry Group (1% Case) for Wholesale Trade ($M)

Region	2020	2030	2040	2050
United States	**-$706.4**	**-$1,891.4**	**-$3,036.1**	**-$4,425.6**
Alabama	-$14.7	-$26.9	-$39.2	-$63.7
Arizona	-$28.2	-$124.9	-$221.6	-$241.2
Arkansas	-$6.1	-$12.2	-$18.4	-$29.4
California	-$42.8	-$144.5	-$333.0	-$168.9
Colorado	-$6.1	-$69.8	-$68.6	-$100.4
Connecticut	-$6.1	-$15.9	-$24.5	-$39.2
Delaware	-$2.4	-$6.1	-$8.6	-$13.5
District of Columbia	-$1.2	-$1.2	-$2.4	-$3.7
Florida	-$113.9	-$181.2	-$247.3	-$348.9
Georgia	-$82.0	-$129.8	-$178.7	-$269.3
Idaho	$1.2	-$1.2	-$1.2	$0.0
Illinois	$6.1	-$12.2	-$74.7	-$209.3
Indiana	-$1.2	-$18.4	-$53.9	-$110.2
Iowa	$2.4	-$3.7	-$14.7	-$31.8
Kansas	-$3.7	-$13.5	-$18.4	-$34.3
Kentucky	-$8.6	-$20.8	-$62.4	-$122.4
Louisiana	-$7.3	-$17.1	-$23.3	-$40.4
Maine	$0.0	-$1.2	-$2.4	-$4.9
Maryland	-$13.5	-$30.6	-$45.3	-$75.9
Massachusetts	-$4.9	-$19.6	-$33.1	-$63.7
Michigan	-$3.7	-$17.1	-$47.7	-$93.0
Minnesota	$0.0	-$13.5	-$40.4	-$88.1
Mississippi	-$2.4	-$7.3	-$11.0	-$19.6
Missouri	-$1.2	-$11.0	-$25.7	-$62.4
Montana	$0.0	-$1.2	-$2.4	-$3.7
Nebraska	$0.0	-$4.9	-$11.0	-$18.4
Nevada	-$7.3	-$34.3	-$88.1	-$58.8
New Hampshire	-$1.2	-$4.9	-$8.6	-$15.9
New Jersey	-$35.5	-$77.1	-$112.6	-$173.8
New Mexico	-$7.3	-$39.2	-$39.2	-$51.4
New York	-$55.1	-$116.3	-$173.8	-$265.7
North Carolina	-$41.6	-$72.2	-$102.8	-$161.6
North Dakota	$0.0	-$2.4	-$4.9	-$8.6
Ohio	-$4.9	-$50.2	-$110.2	-$199.5
Oklahoma	-$18.4	-$72.2	-$47.7	-$85.7
Oregon	$11.0	$12.2	$25.7	$41.6
Pennsylvania	-$39.2	-$83.2	-$120.0	-$184.9
Rhode Island	$0.0	-$1.2	-$2.4	-$4.9
South Carolina	-$14.7	-$24.5	-$34.3	-$52.6
South Dakota	$0.0	-$1.2	-$3.7	-$6.1
Tennessee	-$26.9	-$57.5	-$104.1	-$164.0
Texas	-$104.1	-$264.4	-$318.3	-$484.8
Utah	-$7.3	-$24.5	-$57.5	-$60.0
Vermont	$0.0	-$1.2	-$3.7	-$4.9
Virginia	-$24.5	-$49.0	-$68.6	-$110.2
Washington	$14.7	$17.1	$38.0	$56.3
West Virginia	-$2.4	-$30.6	-$61.2	-$106.5
Wisconsin	$0.0	-$4.9	-$23.3	-$53.9
Wyoming	-$1.2	-$4.9	-$6.1	-$15.9

Appendix F. Loss Function for Small Exceedance Probabilities

Section 2.5 in the body of the report considers the problem of extrapolating the result between the 99% and 1% exceedance-probability interval and the 1% to 0% interval. The 1% to 0% interval is potentially problematic if the value of risk (probability multiplied by consequence) is either not convergent or has a value in excess of that explicitly simulated for the 99% to 1% exceedance-probability range. In this appendix, we develop and justify a functional form for extrapolation based on the underlying analogy of using the logic of a finite resource depletion to represent how the costs of climate change “deplete” the finite GDP.

Because we only address economic impacts, the maximum cost of climate change is limited to the near total loss of the entire GDP of the United States or the GSP (gross state product) of an individual state. In the extreme, with a probability of occurrence approaching 0%, there is the potential of losing most of the economy. We select an upper limit of a 90% loss of the U.S. GDP from the forecast by the macroeconomic referent (discussed in Appendix D). The limit to the maximum loss represents the GDP as if all areas of the United States, in the most extreme case of minimal precipitation, had a climate comparable to New Mexico. This maximum (finite) impact only occurs as the probability approaches zero in the impact distribution, and we assume that the climatic conditions only grow to dominance over the last 10 years of the analysis horizon, i.e., from 2040 to 2050. These assumptions lead to the fraction of loss having the following analytical form:

$$Fraction\ of\ GDP\,Loss\,(t) = 0.0168 * (e^{(\frac{(t-2009)}{41}*4)} - 1), \quad 2010 \le t \le 2050. \qquad \text{(F-1)}$$

The integral of Equation (F-1) and the reference GDP over time is the maximum cost (C_{max}) of the loss in the asymptotically most extreme circumstance, as in

$$C_{max} = \int_{2010}^{2050} Referent\_GDP \times Fraction\ of\ GDP\,Lost \times dt. \qquad \text{(F-2)}$$

The probability of this fractional loss and its attendant risk depends on how fast the tail of the probability distribution falls to zero and how fast the costs rise with the risk variable, for example, temperature or precipitation (Yohe and Tol 2009).

In the absence of technological change, the concept of rising costs as a function of the reduced probability of finding additional (finite) resources emulates the consideration here of rising climate costs as extreme climatic conditions have diminishing probability.

Historically, the finding rate, *R*, for a finite resource was often approximated by an exponentially decreasing function, for example, the barrel of oil found per foot as a function of cumulative drilling feet, *x* (Ghosh and Prelas 2009; Hubbert 1969, 1982; Crovelli 1993):

$$R(x) \propto e^{-ux}. \tag{F-3}$$

The cost, *C*, of finding new resources then exponentially rises as the inverse of the finding rate:

$$C(x) \propto e^{+ux}. \tag{F-4}$$

Per Equation (F-3), the finding rate is a random variable whose values conform to an exponentially declining probability distribution. The change in the probability, *p*, of finding a new unit of oil per foot of drilling is just a scaling of the exponentially declining finding rate in terms of, for example, feet drilled:

$$p(x) \propto e^{-ux}. \tag{F-5}$$

Analogously, the temperature increase from climate change is comparable to the drilling activity (the tail of the distribution of temperature is well approximated by an exponential function); and the exponential cost function corresponds to the exponential damage-function approach recommended by Weitzman (2009). For this analogy to hold in a mathematical sense and establish a finite risk, the probability must fall no slower than exponentially. Because the tail of the gamma distribution of precipitation falls faster than the exponential function, the gamma distribution used to capture the uncertainty in precipitation due to climate change meets this criterion. In other words, the mathematical approach used in this appendix is compatible with the cumulative gamma distribution that describes how fast the precipitation goes to zero and, in tandem, how fast the losses are increasing.

The integral of Equation (F-3) represents the total use of a resource from 0% to 100% of its initial base, while the integration of Equation (F-5) captures the same concept. That is, the total finding of the resource with infinite drilling is the entire resource base, and by the time the probability of finding more of the resource goes to zero, the entire resource base has been exhausted. Equation (F-3) integrates to 100% of the resource base. Equation (F-5) integrates to 100% of the probability of finding the resource.

The resource exploited, *E*, is the integral of Equation (F-3) and a proportionality constant (K_1):

$$E(x) = \int_o^x K_1 \times e^{-ux} dx \tag{F-6}$$

or

$$E(x) = \frac{K_1}{\mu} \times (1 - e^{-ux}). \tag{F-7}$$

The integral from zero to infinity is the entire resource base, *B*:

$$E(\infty) = B = \frac{K_1}{\mu}. \tag{F-8}$$

Therefore,

$$E(x) = B \times (1 - e^{-ux}), \tag{F-9}$$

or

$$1 - \frac{B}{E} = e^{-ux}. \tag{F-10}$$

Define the term $1 - B/E$ as the fraction of the resource remaining, *F*. This term also represents the probability, *p*, of how much of the resource remains to be found at a given level of total drilling.

$$F = p = e^{-ux}. \tag{F-11}$$

Equation (F-3) and Equation (F-5) are equivalent, and we have used the two equations containing both the finding rate and the probability to make functions of the finding rate, *x*, into functions of the probability, *p*. Therefore, the integral of Equations (F-3) and (F-5) allows the transformation of Equation (F-4) from a function of feet-drilled into a function of probability. Equation (F-4) is transformed into a more formal equation with the use of a proportional constant, K_2. Then, substituting Equation (F-11) for the exponential term of Equation (F-4) gives

$$C = \frac{K_2}{p}. \tag{F-12}$$

In the more general case,

$$C(p) \propto \frac{1}{p}. \tag{F-13}$$

Although this exercise uses a concrete example of feet-drilled, the logic applies to any set of relationships where the probability of an occurrence declines exponentially, the consequence increases exponentially, and the integral of all occurrences has a specified finite value (such as the GDP in the actual concern of this study).

We can use C_{max} to limit the maximum value of Equation (F-12) when *p* goes to 0 to obtain

$$C(p) = 1/(\alpha p + \beta), \tag{F-14}$$

where α is the reciprocal of the known loss (e.g., GDP loss at the 1% exceedance probability) times its associated probability. The β term is the reciprocal of C_{max}. The value of α is much larger than that of β. In the absence of β, the loss would go to infinity as the probability goes to 0.0. The β term limits the loss to the maximum it specifies. We can formally derive the functional form of the denominator of Equation (F-14) but here simply state that it has the required mathematical characteristics for our purposes. We use Equation (F-14) to extrapolate the cost, C, or loss over the range of the 1% to 0% exceedance probabilities.

As noted in Section 2.5, the maximum loss is assumed to be 90% of the GDP. From Section 4 of the main text, the simulated 1% exceedance-probability loss is in the range of tenths to a single-digit percentage of the GDP for the nation and the individual states. In using the 1% exceedance-probability cost for determining α, empirically and definitionally α is much larger than β.

Equation (F-14) is the analytical function used for extrapolating costs within the 1% to 0% exceedance-probability interval.

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Appendix G. The Discount Rate with Proportional Costs

As noted in Section 1.2, economic studies use a discount rate to assign a value in the present to costs that will occur in the future. Also as noted in Section 1.2, the determination of the discount rate is often represented by the equation

$$r = p + \theta * g. \tag{G-1}$$

Here, r is the social discount rate, p is the pure rate of time preference (PRTP), θ is the income elasticity of the marginal utility of consumption, and g is the growth rate in per capita consumption. Cline (1992) provides a relatively complete derivation of Equation (G-1), but Cline's derivation is based on absolute (or additive) costs. With precipitation as the primary uncertainty, the damage costs are proportional to the size of the economy, and the justification for the θ in Equation (G-1) may be absent. This appendix provides one justification for disregarding θ under such situations.

If the costs associated with climate change have a positive or negative effect on the economy, the emphasis on future, richer generations having a better ability to cope with climate-related costs may have some merit. (Note that this approach disregards concerns that the ecological footprint of humankind indicates increasing consumption may be unsustainable even into the midterm future [Wackernagel et al. 2002; Lenzen and Murray 2003]). If the costs are proportional to the existing economy, Cline's (1992) derivation may not apply as the equations below indicate.

If the utility, U, of consumption, C, is

$$U \propto K \times C^{\alpha}, \tag{G-2}$$

where $0.0 < \alpha < 1.0$, and K is a constant, and if consumption is a share, S, of the economy, and if the climate impacts are proportional, F, to the size of the economy, then the fractional change in utility is

$$\Delta U / U = K(C^{\alpha} - (1 - S \times F) \times C^{\alpha}) / (K \times C^{\alpha}) \tag{G-3}$$

or

$$\Delta U / U = S \times F. \tag{G-4}$$

Therefore, the change in utility is independent of the level of consumption, contrary to the implicit assumption in Equation G-1.

An allometric function (econometrically estimated as a log-linear function), such as that represented by Equation G-2, commonly describes economic data. Monetary value is a relative concept. A dollar in 1920 had much more buying power than a dollar today, but it could not buy the conveniences we have today. Proportional measures of value maintain their meaning whether measured in yen or dollars, in the year 1850 or 2050. Using the conventional assumptions of a homogenous population and the allometric representation for the utility of consumption (Equation [G-2]), Equation [G-4]) indicates that a 20% loss in consumption for Warren Buffet is the same proportional loss in utility as a 20% loss to a minimum wage worker. Such a proportional loss is independent of the level of consumption, and thus the utility is not a function of income levels. Although it is possible to argue that increased temperature has positive or negative impacts, this study shows that the impact of reduced precipitation is clearly proportional. Therefore, the second term in the discount equation becomes questionable at best and possibly not applicable. As such, only the PRTP term may have meaning, and as noted above, some economists rationalize its value as being close to zero (Quiggin 2008).

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