ANL-16/17

Climate Models Datasets for Climate Assessments: A Summary for the State of Maine

Environmental Science Division

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prepared for
Department of Homeland Security Maine Climate Change Adaptation
Regional Resiliency Assessment Program

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1 INTRODUCTION

The Department of Homeland Security (DHS) Regional Resiliency Assessment Program (RRAP) project Casco Bay, Maine, Climate Change Adaptation was initiated in 2013. The project's foundation is a stakeholder-driven assessment of community and infrastructure vulnerabilities that includes development of adaptation data and methodologies.

This report is one of the supporting documents produced for identifying resources, primarily climate model output, to assist in impact assessment modeling and in developing adaptation strategies for the local communities. It is expected to provide the necessary background for obtaining datasets that support this effort. Although it is not designed to be a how-to manual, we hope to provide sufficient information that could be used to plan a detailed impact assessment for infrastructure, hydrological, and ecological systems.

National and international organizations have created a number of documents that provide information for developing impacts, assessing vulnerability, and assisting decision makers. The goal of these documents is to assist in choosing the right set of tools, datasets, and models for framing climate change impacts for further consideration. Although many such assessments are geared toward global impacts and policymakers (e.g., Intergovernmental Panel on Climate Change [IPCC] assessment reports), there has been an increased focus on regional-scale impacts and datasets. The IPCC Fifth Assessment Report has an extended discussion on regional-scale climate change and its impacts (Hewitson et al. 2014; Revi et al. 2014). Separate reports on regional-scale impacts have been generated by the World Meteorological Organization (WMO) and IPCC (Watson et al. 1998; Giorgi et al. 2001; Adams et al., 2013).

The U.S. Global Change Research Program (USGCRP) has undertaken the responsibility of performing regional-scale assessments of climate change across the United States and a third report from this process was released in 2014 (Melillo et al. 2014). Efforts to produce guiding sub-regional-scale documents and reports at the level of states and cities has been a focus in recent years, and several such reports have been produced (Hayhoe et al. 2008; Wuebbles et al. 2010). Application of these assessments to impact and adaptation has been inconsistent. The primary demand for this type of research has come from the hydrological and ecological communities. A few case studies and study criteria for applying climate model projections to impact and assessment studies have been developed by organizations such as the World Bank (Girvetz et al. 2012), United Nations Environment Program (UNEP), and the United Nations Food and Agriculture Organization (FAO) on global scale. Regional and sub-regional-scale processes are under development.

The focus of this document is to provide sufficient background information on applying primarily downscaled climate model output for impact assessment and adaptation studies for the state of Maine.

2 CLIMATE CHANGE IMPACTS

Climate change affects every aspect of the earth and the activities of humans. This document addresses specific problems that are primarily concerned with planning/building and maintaining critical infrastructure. Some of these key sectors, expected problems faced by them due to climate change, and their expected data needs are discussed below.

This report addresses the Energy, Transportation, and Water sectors. Each of these sectors has different climate change risk profiles that are related to their planning horizons, their demand and distribution needs, and the geographical location of the infrastructure maintaining these services.

2.1 Energy

Climate change impacts on the energy sector include changes in demand, grid resilience under increased demand, effects of severe weather events (hurricanes, snow storms, and ice storms) on infrastructure, the nexus between availability of water for certain power producing activities and energy production (DOE 2013), and the resilience of power grid infrastructure under changing climatic conditions. Each of these impacts requires a different set of climate data products. The evaluation of changes in demand requires climate model projections of number of heating degree days (HDDs)/cooling degree days (CDDs) and the consequent demand for cooling or heating (Deschênes and Greenstone 2011; Franco and Stanstad 2006; Isaac and van Vuuran 2009; Jaglom et al. 2014). The second primary data need for evaluating power sector impacts is the possible changes in extreme events (e.g., heatwaves, floods, and droughts; DOE 2013). The availability, quality, and temperature of water can have significant impacts on power generation from thermoelectric, hydroelectric, and biofuel production (DOE 2014).

2.2 Transportation

The transportation sector is primarily concerned with its infrastructure's resilience to climate change and to the impacts of extreme events. Projections of changes in sea level rise, precipitation during different times of the year, changes to thaw and freeze cycles, changes in the intensity of precipitation, and changes in number of days with higher/colder temperatures are all required for assessment of infrastructure reliability. Changes in the frequency, location, and intensity of extreme events are additional significant inputs to the assessment of the transportation sector's resilience to climate change (NRC 2008; Melillo et al. 2014).

2.3 Water/Wastewater

Climate change impacts on the hydrological cycle and water resources have been the focus of a number of studies (IPCC 2014, Melillo et al. 2014). One of the most widely recognized changes in climate is the change in precipitation, and changes in its patterns, intensity, and frequency. The primary variables for conducting assessments of the water sector include precipitation-related variables, changes in surface temperature, landuse/landcover changes, and changes to water demand.

3 ANALYSIS PATH

Analyzing the impacts due to climate change, analyzing the vulnerability of a sector/region/system to the impacts, and developing an adaptation strategy involves many steps with varying demands on data, models, and resources. A scenario analysis is often the first step to developing possible impacts due to climate change, followed by analysis of impacts and vulnerability and development of adaptation planning options (Figure 1).

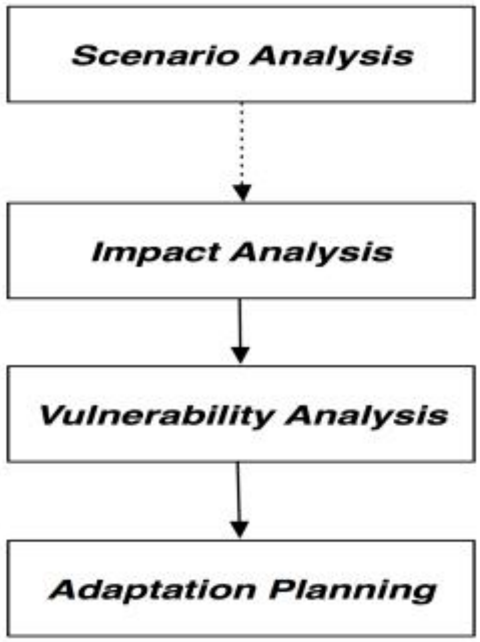

FIGURE 1 Possible Path for Implementing Climate Impacts Assessment and Adaptation Planning (A preliminary assessment that develops potential impact scenarios to assess the importance of climate change for a given impact sector/ facility would lead to further detailed analysis. Vulnerability and impact analysis of the infrastructure/sector will require further climate model inputs and analysis tools and data resources.)

3.1 SCENARIO ANALYSIS

A first step in assessing climate change impacts is performing a scenario analysis. Developing scenarios of future probabilities for impact sectors such as hydrology (Wilby and Harris 2005) and ecological sustainability (Bohensky et al. 2011) are examples of this approach. In this type of analysis, climate change scenarios provide one of several sets of inputs for projecting a possible future and are useful for assessing the significance of climate factors as compared to other factors that may have a bigger influence on the future scenarios. For example, the impacts of population changes may be bigger than or equal to those due to climate change (Vorosmarty et al. 2000). Scenario-building exercises can be quite involved (Hulme et al. 1999; Winkler et al. 2011) and can be conducted at a regional level, for example, at the level of a watershed. Scenario analysis is a suitable approach when the overall system-scale uncertainties are significant and uncontrollable (Peterson et al. 2003). An example of this type of analysis is that of Bohensky et al. (2011), which discusses potential damage to the greater barrier reef under changing climate conditions in relation to other socioeconomic changes at regional scale in Australia. Uncertainty plays a key role in developing the socioeconomic scenarios for the future, as well as the climate change drivers. The analysis leads to a set of probable future scenarios that could then be used for future planning. Scenario approaches are best suited for analyses when the uncertainties are significant and the expectation of reducing them is limited (Peterson et al. 2003). Figure 2 follows the discussion in Hulme et al. (1999).

3.2 IMPACTS AND VULNERABILITY

The IPCC defines climate impact as the effects on human and natural systems due to extreme weather, climate events, and climate change. The vulnerability of a system is defined as the predisposition of the system to be adversely affected. Therefore, vulnerability is correlated with the capacity to cope with and adapt to the impacts. Climate change impact assessments proceed by first identifying the problem or sector on which to focus. The problem identification should lead to the selection of a geographical region and a time horizon over which the impacts need to be assessed. The primary inputs to climate impact assessments are the projections of climate change and their associated uncertainties. Projections generated using climate models have several uncertainties. The left column in Figure 3 lists three primary uncertainties: (1) scenario uncertainty, (2) model uncertainty, and (3) internal variability. Projections created by climate models include all of these uncertainties. Climate models are used to produce projections under varying greenhouse gas (GHG) forcing scenarios developed by a community of independent scientists (van Vuuren et al. 2011). The model-generated outputs for the analysis time slice are bias corrected[1] and if necessary downscaled[2] to the appropriate spatial location and

[1] Bias correction—in assessments of climate impacts, a general practice to account for the differences between models and observations is to calculate the difference between a model and observations using historical records, applying this correction to projections of the future by that particular model.

[2] Downscaling—the process of disaggregating global climate model projections that have coarse spatial resolution to smaller spatial scales using historical observational data (statistical downscaling) or using a model that has similar physics as the global model at a higher spatial resolution and over a smaller domain, such as the size of a country or a continent (dynamic downscaling).

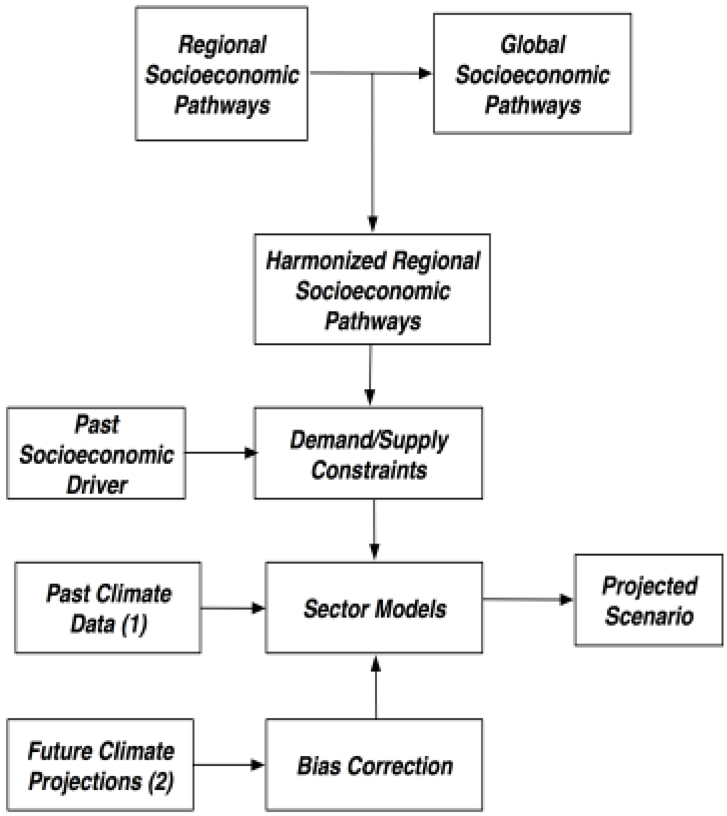

FIGURE 2 Scenario Analysis (Combined with a sector model, socioeconomic scenarios lead to the development of various scenarios that can be used to estimate impact. Climate change with either extrapolated changes from past climate data or future projections generated from climate models is added to the analysis to evaluate the impact of climate change on a sector.)

resolution and used as inputs to a sector model for developing the impact analysis. We discuss each of the items in Section 3.2.3.

3.2.1 GHG Scenarios

Projection of climate change as a result of increased GHGs on the earth system first requires estimates of concentrations or emissions of GHGs in the future. The GHGs of concern are produced primarily as a result of the use of fossil fuels by industry, transport and power generation. In scenario development, the use of fossil fuels is linked to economic activity in a part of the world, population density of that region, and other socioeconomic factors. Developing emission estimates for the future thus requires projections of population dynamics, economic

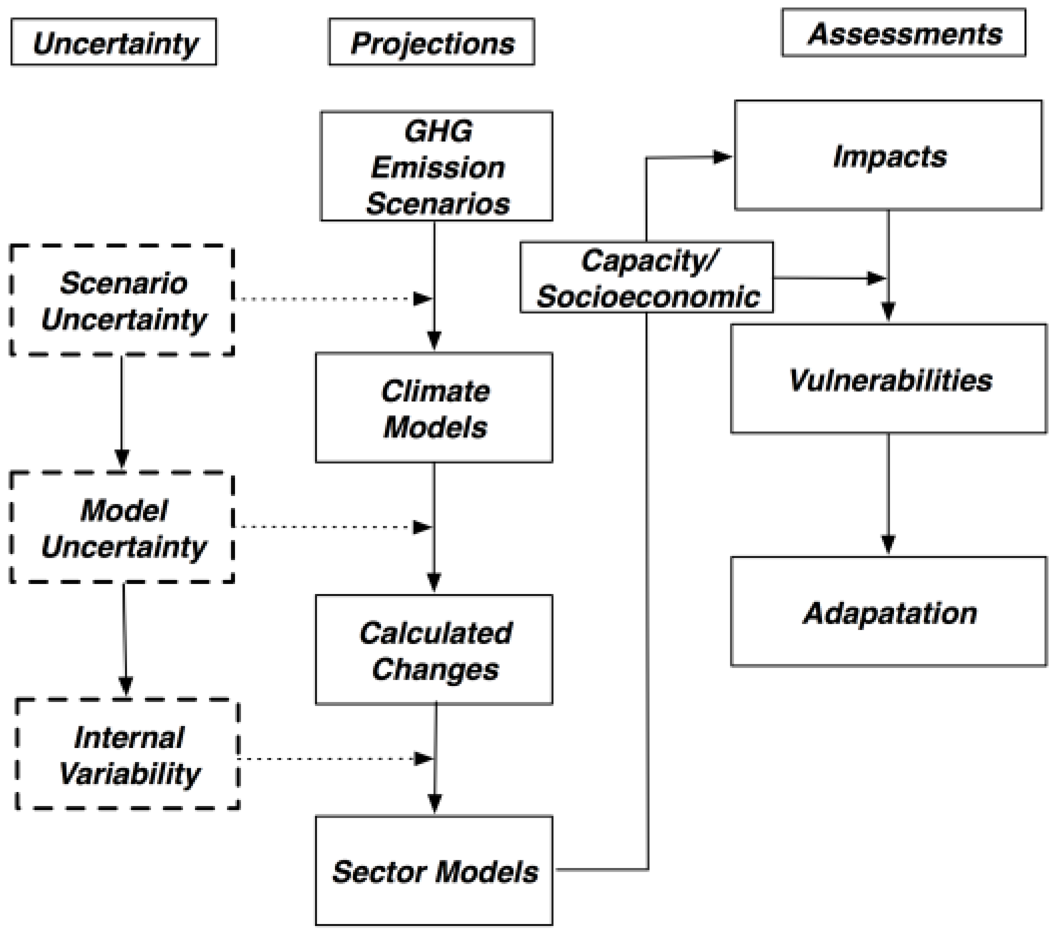

FIGURE 3 Pathway for In-Depth Impact, Adaptation, and Vulnerability (IAV) Analysis (This requires additional input from climate models, uncertainties in projections, sector models, and socioeconomic models to perform the analysis.)

development, transportation demand, and transportation modes to develop estimates of fossil fuel use by various sectors of the economy in a particular region. An international community of scientists addressed this task by developing a number of scenarios that describe development pathways for various parts of the world for the next several decades through the end of the 21st century. These scenarios are then used in a model that integrates socioeconomic data and simple representation of climate to capture the feedbacks between economic decisions and climate change to develop GHG emission profiles. These models are known as integrated assessment models, and they vary in complexity from very simple (e.g., Dynamic Integrated Climate-Economy Model [DICE]) to very detailed (Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE); Global Change Assessment Model (GCAM), etc.). For the current IPCC assessment, a total of 70 such scenarios were developed. Climate models in general do not simulate all 70 scenarios, but include a representative selection of a family of scenarios that lead to approximately similar levels of GHG emissions at the end of the

21st century. Four of the most widely used of these scenarios, referred to as the Representative Concentration Pathways (RCPs), are shown in Figure 4.

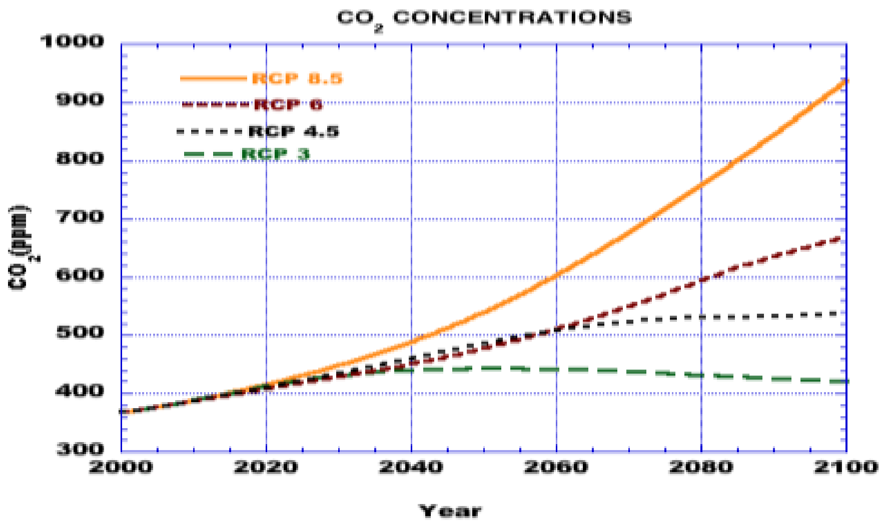

FIGURE 4 Concentration of CO_2 (in parts per million, ppm), the Primary Anthropogenic GHG from 2000 to 2100, for Four Scenarios Commonly Used as the GHG Driver by Climate Models (The model output from these four scenarios is adjusted for bias, downscaled, and then used as input for impact assessments. The four pathways are RCP 8.5 [orange, solid line], RCP 6.0 [red, dashed line], RCP 2.6 [green, long-dashed line], and RCP 4.5 [black, dotted line]. The number at the end of each of these pathway designations refers to the amount of heating per square meter estimated by the end of the century when these GHG concentrations are used in a climate model.)

3.2.2 Climate Models

Climate models, developed in the early 1970s, use physical principals to represent the atmosphere at a global scale. They have been continually improved over the past four decades. The latest versions of the models are designed to represent the atmosphere, ocean, and the biosphere together and are referred to as earth system models (ESMs). These complex models represent hundreds of physical, chemical, and biological phenomena that occur at all times around the globe and determine the physical, chemical, and biological state of the atmosphere, ocean, and biosphere. The most recent evaluation of these global climate models (GCMs) included 40 different models (Flato et al. 2013). The evaluation concluded that these models can predict the change in surface temperature over the recent past with high confidence. The current generation of models have improved surface temperature predictions and small improvements of precipitation prediction, compared to the previous generation of models. These models operate at a spatial grid resolution between 100 km^2 and 300 km^2. The physical processes represented in these models are continuously improved by the respective model development teams. One of the major goals of the new model development is to obtain a higher spatial resolution. It is expected that in 5 to 10 years, GCMs with spatial resolutions of 25 km^2 or finer will be available (ACME 2014).

3.2.3 Uncertainties

As discussed in Section 3.2, climate model projections have three primary types of uncertainties: (1) scenario uncertainties, (2) model uncertainties, and (3) internal variability. Figure 5 shows that if the sum of all uncertainties is one, the fraction contributed by the scenario uncertainty is the largest toward the end of the century. The model internal variability causes the highest uncertainty at times closest to the present and the model uncertainty remains constant or slowly decreases throughout the entire projection period.

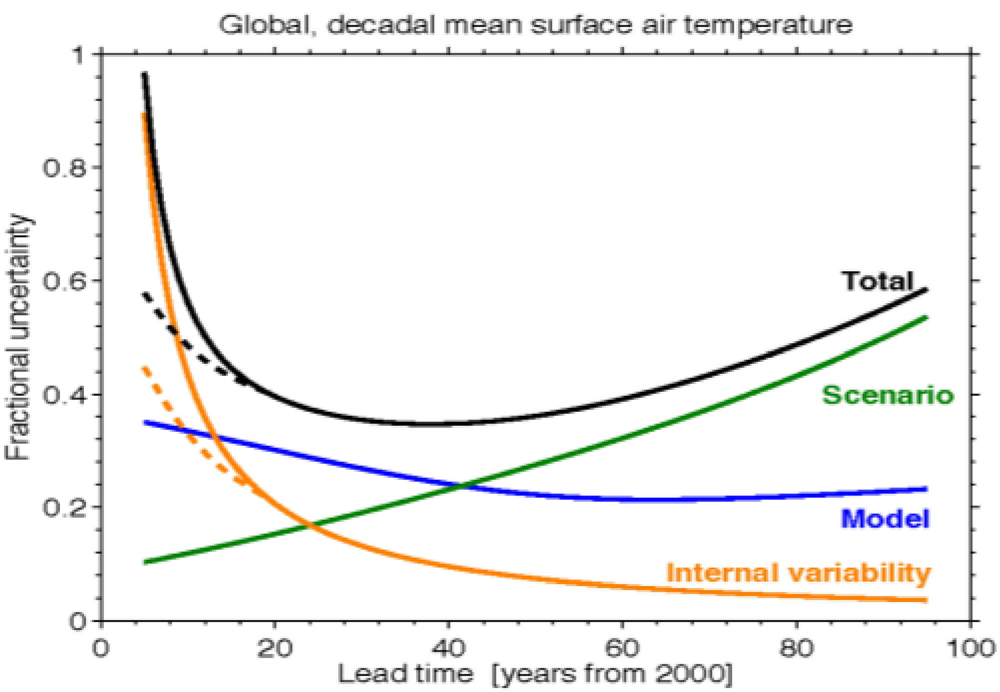

FIGURE 5 Nominal Representation of Climate Model Uncertainties in Projected Surface Air Temperature (Hawkins and Sutton 2009; ©American Meteorological Society. Used with permission)

3.2.3.1 Scenario Uncertainty

As discussed in Section 3.2.1, GHG emission scenarios are generated for different socioeconomic scenarios. For consistency, the emissions are scaled to known emissions from the present and recent past. Therefore, near-term uncertainty from these emissions is not significant and does not contribute significantly to model projections of climate change close to present day. However, the assumptions of the scenarios used to generate these emissions diverge from each other regarding fossil fuel use, technology, and other socioeconomic factors. As a result, the estimated emissions for each of these scenarios start diverging from each other after a few decades, and the divergence is significant by the end of the century. Climate modelers addressed this uncertainty by modeling a select number of emission scenarios that provide a reasonable coverage of the emission uncertainty at the end of the century. Most available model output is for the four scenarios shown in Figure 3. The impact assessments use output from each of these models to cover the range of scenario uncertainty.

3.2.3.2 Model Uncertainty

Climate models represent many of the physical, chemical, and biological processes that make up the earth system and its interactions with incoming solar radiation. The models use fundamental principles of physics, chemistry, and ecology to represent known processes. However, there are a number of phenomena that occur at spatial scales below those that are resolved in the current generation of climate models, for example, the formation of clouds. Several types of clouds are formed by physical processes that occur at very small spatial scales (hundreds of meters to kilometers), which are below the 100-km threshold of many current-generation climate models. These unresolved processes are represented in models using a parametric approach. This introduces uncertainty, because the parametric models are only as good as the available observations that form the basis for developing the parameterizations. As we gather more intensive observations of such processes, the models representing them are constantly improved. This is expected to reduce model uncertainty.

At the present time, the model uncertainty for use in impact assessments can be represented in two ways: (1) generating a physical ensemble simulation with a single model to provide an uncertainty estimate for that model or (2) using results from multiple models that most likely have different parametric representations of a physical process. Although the former output may be more desirable for understanding the uncertainty in each model, this type of model is fairly expensive to produce, because the parameter range of each parametric model and the number of parametric models in a typical climate model can be fairly large. It is likely that the information from the latter will be more readily available to a user interested in impact assessments. As discussed in section 3.2.2, approximately 40 models were used in the most recent IPCC assessments and could be used to explore model uncertainty for impact assessments. However, most users pick a few models that are representative of the range of model responses to GHG emissions. The selection of models for this purpose is discussed further in Section 5.

3.2.4 Internal Variability

Near-term climate projections are dominated by the internal variability of the models (Hawkins and Sutton 2009; Deser et al. 2012). GCMs are based on numerical equations and require the description of the initial state of the atmosphere, ocean, and biosphere to start the model calculations. The equations that describe the various interconnected process in the earth system give rise to slightly different climate projections as the simulation progresses when slightly different initial conditions are used in the same model. An ensemble of model simulations with small changes in initial conditions could give rise to differences in projected surface temperature at a given location for up to 30 years from the start of the simulations (Deser et al. 2012). This internal variability tends to be higher as the geographical location over which this analysis is performed gets smaller. As shown in Figure 5, internal variability is a dominant factor in the first few years from the start of the simulation and decreases or becomes less important as the time of integration increases. Another way to understand this would be to think of this as day-to-day and year-to-year noise produced within the atmospheric system that will be higher when we look at small spatial scales (e.g., city) compared to a region (e.g., state scale).

3.2.5 Bias Correction

A critical step in using climate model projections for impacts assessments is the correction for model bias. Bias corrections are usually applied when assessing hydrological impacts. The model bias is defined as the difference, when averaged over several years, between a chosen set of observations and calculated values from a model at the appropriate spatial scale. The choice of time period over which the average bias estimate is generated is constrained by the availability of observations, and a 30-year band covering the most recent historical period is used. Figure 6 is an example of this process. The left side shows monthly average precipitation from observations over a model grid cell in Portland, Maine (orange, solid line); the green, dashed line represents the averaged model precipitation over the same region, averaged over the spring months, for 30 years. The figure on the right is another example of the model−observation difference, as a distribution of bias over the same 30-year period in the Great Plains (GP) region in the form of a box plot. Each of the colored boxes represents a different model simulation for the 30 years separated into the four seasons.

3.2.6 Downscaling

All climate projections originate with coupled atmosphere-ocean GCMs. These models are driven by scenarios of future concentrations of GHG and other radiatively active substances; they generate projected changes in atmospheric, oceanic, and surface climate variables at scales typically ranging from 100 to 300 km. Because these spatial scales are typically insufficient for accurate simulation of regional conditions, generating climate projections at a regional level requires some method of downscaling, generally either based on an RCM (dynamic downscaling) or empirical methods based on empirical approaches that use climate model outputs and climate observations (statistical downscaling).

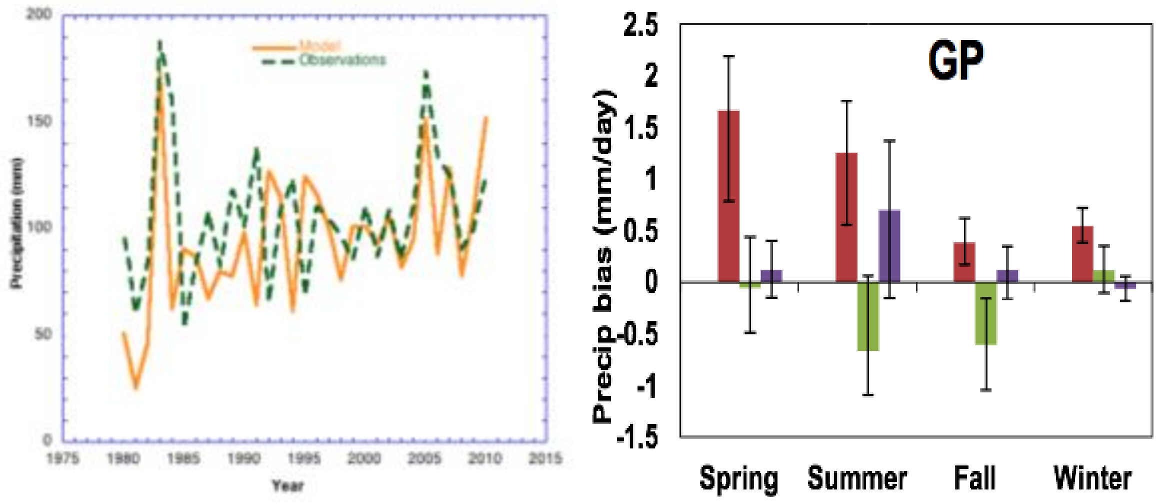

FIGURE 6 Process for Estimating Model Bias (The left panel shows the average precipitation in spring over a single model grid cell [Portland, Maine] in millimeters from observations and model simulations. The right panel shows the bias estimated from three model simulations over the four seasons as a box plot for the GP region. The error bars denote the annual distribution of bias at the 10th and 90th percentiles.)

Statistical downscaling can be relatively inexpensive, compared to the use of RCMs, when applied to just a few locations or with simple techniques. The statistical downscaling technique generally does not add any new information compared to the host climate model and is suitable for generating quick assessments. Statistical downscaling represents the process of obtaining fine grid output from coarse grid output by using statistical fits for current climate observations. This method can be tuned to obtain finer resolution output for targeted variables and for selected locations. The ease of use of this method, and its flexibility, has led to a wide variety of applications for assessing impacts of climate change (e.g., Kattenberg et al. 1996; Hewitson and Crane 1996; Giorgi et al. 2001; Wilby et al. 2004, and references therein). Approaches encompass a range of statistical techniques, from simple linear regression (e.g., Wilby et al. 2000) to more complex applications based on weather generators (Wilks and Wilby 1999), canonical correlation analysis (e.g., von Storch et al. 1993), or neural networks (e.g., Crane and Hewitson 1998). These methods have been successfully used for generating regional climate assessments for various governmental agencies and national reports. Figure 7 shows statistically downscaled results for the upper Mississippi catchment region produced using the Community Climate System Model (CCSM3.0) model used in the Coupled Model Intercomparison Project (CMIP3) assessment. Two time periods, 2021–2030 and 2051–2060, were used to perform statistical downscaling using approximately 130 weather stations in this region. Percent changes in precipitation for these two decades, compared to historical averages from observations, are presented in Figure 7.

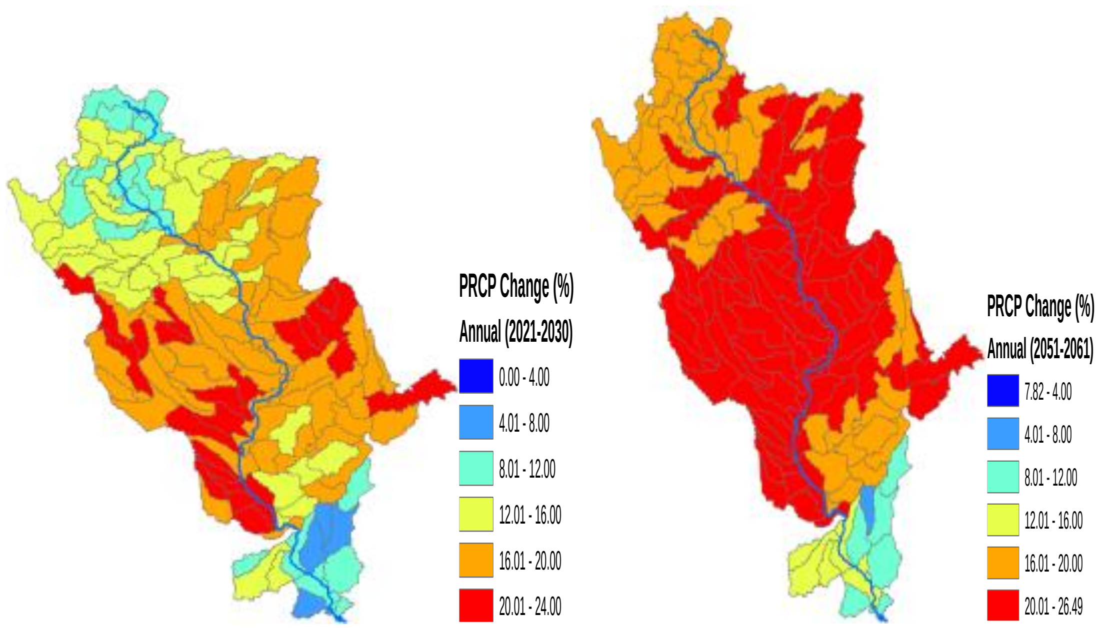

FIGURE 7 Statistical Downscaling of Precipitation for the Upper Mississippi Basin from a GCM (Franklin et al. 2010) (The host climate output is from CCSM3.0 simulations for the A1B scenario generated for the IPCC AR-4 and archived at the Earth System Grid [ESG] website.)

Dynamical downscaling by RCMs generally refers to the use of limited area climate models that are forced at the boundaries using results from a host GCM (Giorgi and Mearns 1991; McGregor 1997; Giorgi and Mearns 1999; Wang et al. 2004; Liang 2005). These models were primarily developed by adapting mesoscale meteorological forecasting models to climate simulations. As a result, they have a full description of the land surface process, detailed cloud physics, and radiative transfer schemes (Giorgi et al. 2012). The higher spatial resolution of RCMs, as compared to GCMs, generally improves the ability to simulate climate, especially for fields such as precipitation that have high spatial variability. For example, some studies show that the higher RCM resolution yields better monsoon precipitation forecasts and interannual variability (Mo et al. 2005) and precipitation intensity (Roads et al. 2003). Thus, RCMs can be used effectively to produce a more accurate forecast at regional scales in many instances. These models have been used widely in applications that require regional resolutions, and in particular where there is a need for higher resolution climate projection for estimating hydrological vulnerabilities (Kenton et al. 2012; Chan et al. 2014, Mejia et al. 2012, Mearns et al. 2015).

Figure 8 illustrates a flowchart showing the process for creating a dynamic downscaled product. The process starts by using the chosen RCM to perform a simulation over a time slice that has sufficient observational data to estimate bias in model calculations. The model requires three-dimensional preconditions for initialization and boundary conditions that will be regularly updated during the model simulation. Because the model only covers a fraction of the globe, the boundary conditions provide the inflow from regions outside the model domain into the model. These inputs are regularly updated so that the model experiences the same large-scale

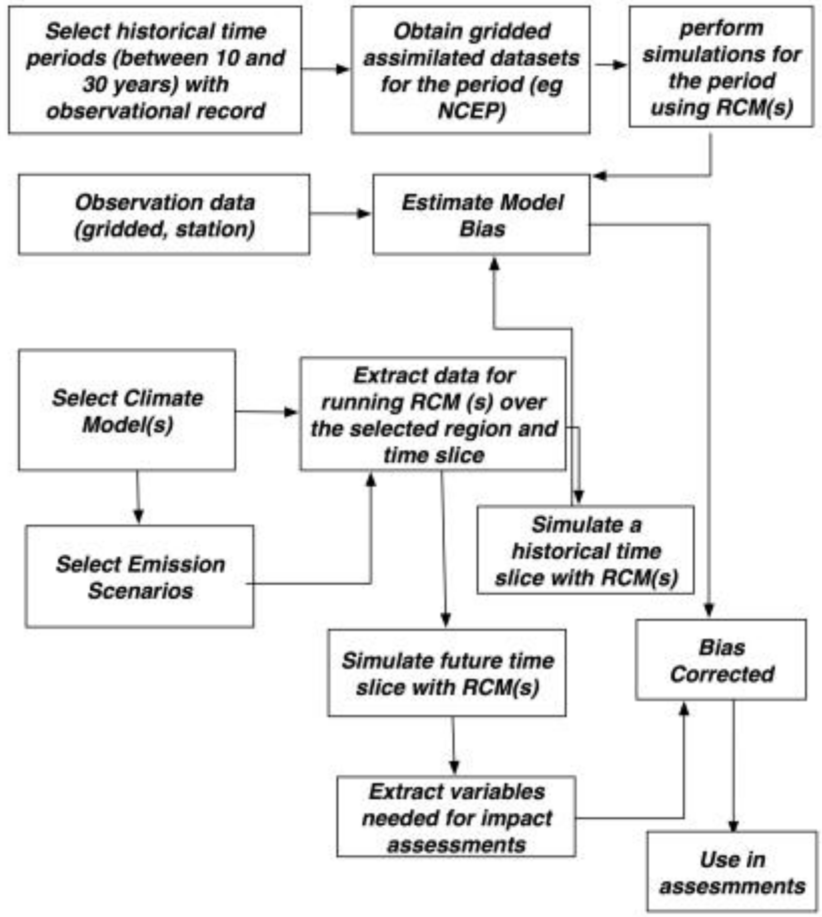

FIGURE 8 Dynamic Downscaling Process

phenomena observed. These historical model simulations are used to estimate the model bias. Observational datasets include observations from weather stations maintained by the National Weather Service, and further processed to generate daily, monthly and seasonal average observation files. The Precipitation-Elevation Regressions on Independent Slopes Model (PRISM) data is one such example. The next step involves selecting a future time slice over which to employ the RCM. Typically, RCMs are not used to simulate from present to 2100 as one continuous simulation; at present, this tends be computationally unfeasible at spatial resolutions lower than 50 km. Therefore, time slices of 10 years or more distributed around mid-21st century and the end of the 21st century are typically chosen for generating the projection simulations. The input fields for these model runs are obtained from pre-existing global-scale simulations that are archived in repositories, such as CMIP5. These input conditions can be adjusted for estimated bias, as described in Section 3.2.5, before input to an RCM or after the simulation results are obtained. One critical consideration for generating the downscaled model results is the choice of the GHG emission scenario for which the GCM results are available. The choice is made to meet the needs of the analysis and to match the number of such simulations that can be performed with available resources.

4 CLIMATOLOGY OF MAINE

Here we discuss the climatology of Maine based on observational datasets of the recent past and model simulations. This discussion aims to provide context for evaluating climate change around mid-century and end of the century for Maine. We use datasets and model simulations from 1980 to 2009 to discuss the baseline climatology. A more general description of the northeast climate is provided in Kotamarthi et al. (2016). As noted in Kotamarthi et al. (2016), in general the GCMs participating in the CMIP5 models have a small dry bias over this region during winter and small wet bias during the summer (Sheffield et al. 2013). The surface temperature shows a small bias toward warmer temperatures in both winter and summer. Below, we discuss the results from regional-scale models, selected GCMs, and observations for the state of Maine.

Figure 9 shows the 30-year average precipitation in both summer and winter months. The data is from PRISM developed by Daly et al. (1994, 1997, 2008). The PRISM values, which are corrected for systematic elevation effects on precipitation climatology, provide observation-based temperature and precipitation on a grid mesh of 1/8° latitude × 1/8° longitude that covers the continental U.S. (CONUS). The precipitation data includes both solid (e.g., snow) and liquid (e.g., rainfall) precipitation. Precipitation in winter months is mostly snow, which averages 2.5–3 mm/day over southern Maine and 2–2.5 mm/day over northwestern Maine. There is more precipitation in summer months than in winter, 2.5–3.5 mm/day over most of Maine, and more than 3.5 mm/day over northwestern Maine.

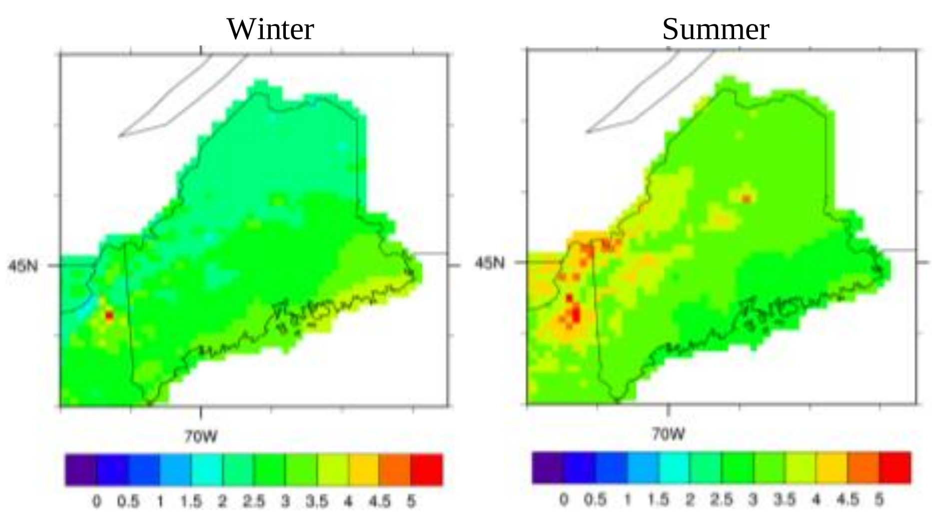

FIGURE 9 Observed 30-year (1980–2009) Average Daily Precipitation (mm/day) in Maine in Winter and Summer

Figure 10 presents the 30-year average near-surface air temperature in summer and winter months. In the winter, the temperature is lower than minus 10°C (~15°F) for northern Maine and minus 6°C (~21°F) for southern Maine. In the summer, the daily average temperature is 15–17°C (~60°F) for northern Maine and 18–19°C (65°F) for southern Maine.

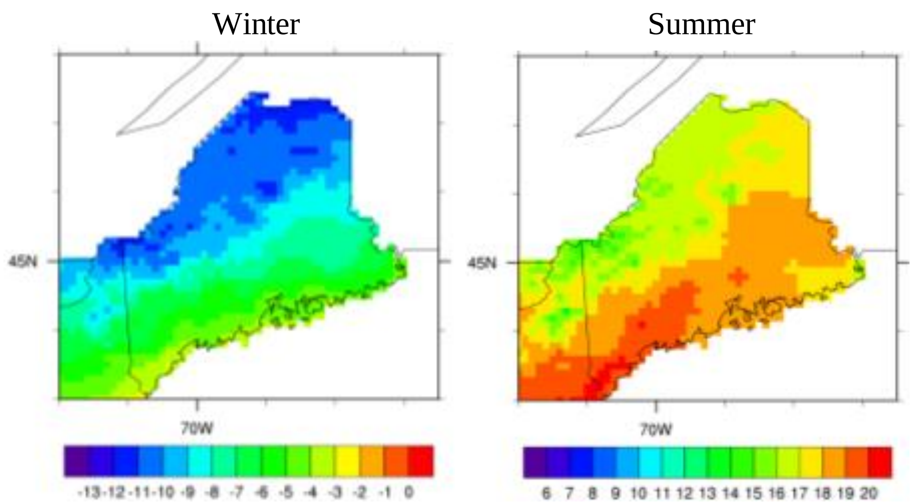

FIGURE 10 Observed 30-year (1980–2009) Average Temperature (°C) in Maine in Winter and Summer.

4.1 FREQUENCIES OF EXTREME EVENTS IN HISTORICAL DATASETS

The climatology of extreme temperature and precipitation events is discussed below. Figure 11 shows the number of wet days, defined as days when precipitation was heavier than 10 (left panel) and 20 mm (right panel) per day (~0.5 to 0.8 inches of rainfall). In general, there are more heavy precipitation days in southern Maine than in northern Maine. For example, there are 25–35 days with more than 10 mm of precipitation over all of Maine, but more than 35 days in some locations in southwestern and southeastern Maine. There are only 5–10 days with more than 20 mm of precipitation in northern Maine and 10–15 days in southern Maine.

Figure 12 shows dry days, defined as the days with less than 0.1 mm of precipitation (trace amounts of rainfall). In general, there are more days with less than 0.1 mm precipitation in southern Maine than in northern Maine. Compared with Figure 10, this indicates that in southern Maine, it is often either dry or raining/snowing heavily at a rate greater than 10 mm per day. In contrast, in northern Maine there are more moderate precipitation days (drizzle) than very dry (<0.1 mm) or very wet (>10 mm) days.

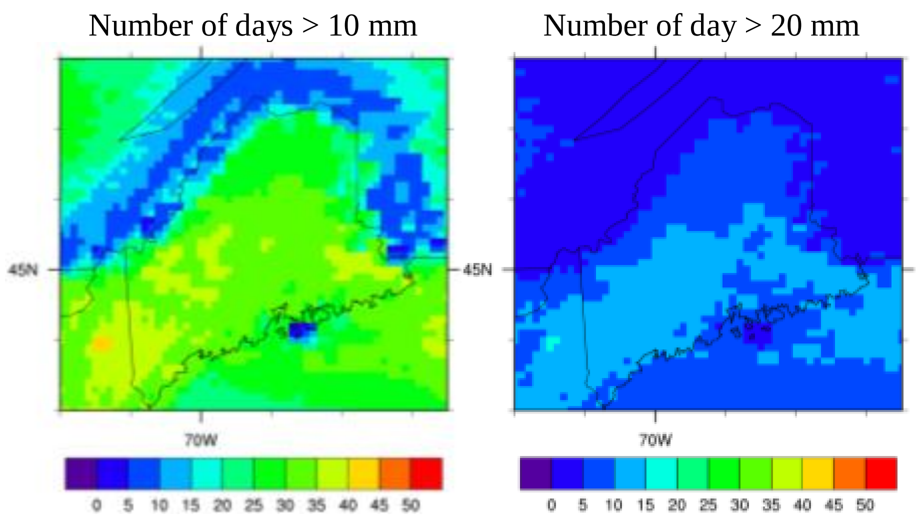

FIGURE 11 Observed Number of Days in a Year (30-year average) with Daily Precipitation Exceeding 10 mm (left) and 20 mm (right)

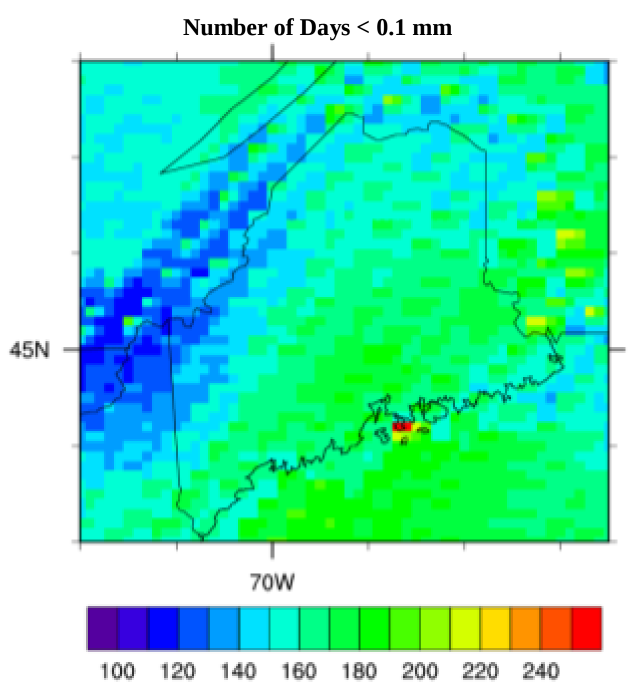

FIGURE 12 Observed Number of Days in a Year (30-year average) with Daily Precipitation Less than 0.1 mm

Figure 13 shows the average number of hot and very hot days in a year, defined as days with a maximum temperature higher than 27°C (80°F) (left panel) and 29°C (85°F) (right panel). The data comes from North American Regional Reanalysis (NARR), and indicates daily temperature at a spatial resolution of 32 km. In general, days with a temperature higher than 29°C (85°F) are rare, but days with a temperature higher than 27°C (80°F) are more common. For example, there are only 1–2 days per year with a temperature higher than 29°C (85°F) over northern Maine, while there are 4–8 days per year with a temperature higher than 27°C (80°F). In southern Maine, there are only 2–4 days per year with a temperature higher than 29°C (85°F), while there can be 10 to 20 days with a temperature higher than 27°C (80°F).

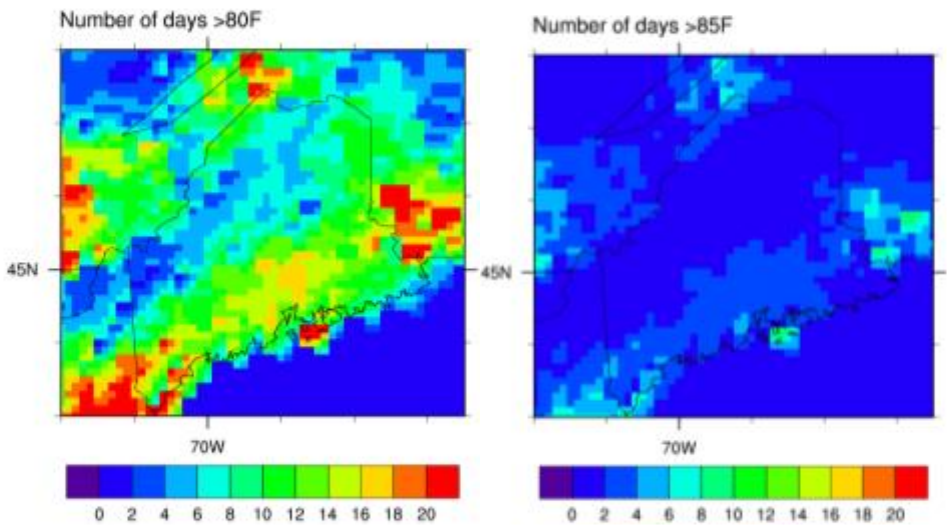

FIGURE 13 Observed Number of Days in a Year (30-year average) with Daily Maximum Temperature Higher than 27°C (80°F) (left) and 29°C (85°F) (right)

Figure 14 shows freezing days and extremely cold days, defined by number of days with minimum temperatures below 0°C (32°F) (left panel) and lower than -18°C (0°F) (right panel). There are 150 days each year with a temperature lower than 0°C (32°F) and more than 28 days with temperature lower than -18°C (0°F) over northern Maine; this corresponds to about 5 months and 1 month per year, respectively.

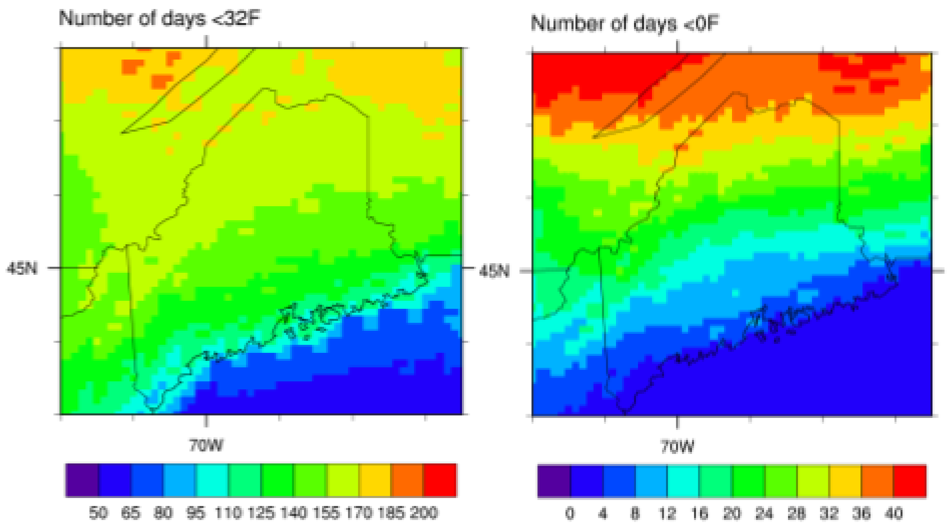

FIGURE 14 Observed Number of Days in a Year (30-year average) with Daily Maximum Temperature Lower than 0°C (32°F) (left) and -18°C (0°F) (right)

4.2 OBSERVED CHANGE IN CLIMATE OVER THE PAST 30 YEARS

We performed a preliminary analysis using observational data to identify trends or lack of trends in surface temperature and precipitation for Maine in general and Portland in particular. Figure 15 shows the variability of annual mean precipitation, summer precipitation, and winter precipitation. The blue line represents the average for Maine, and the red line represents the location approximate to Portland. The dashed lines indicate the 30-year trend of the annual variations, and the equations describe the trend line. While there is important annual variability of the precipitation, there are also increases for both summer and winter precipitation, especially winter precipitation, which shows an increase of 1.6 mm per year over Portland.

The annual variability of annual mean, summer, and winter temperature is shown in Figure 16.

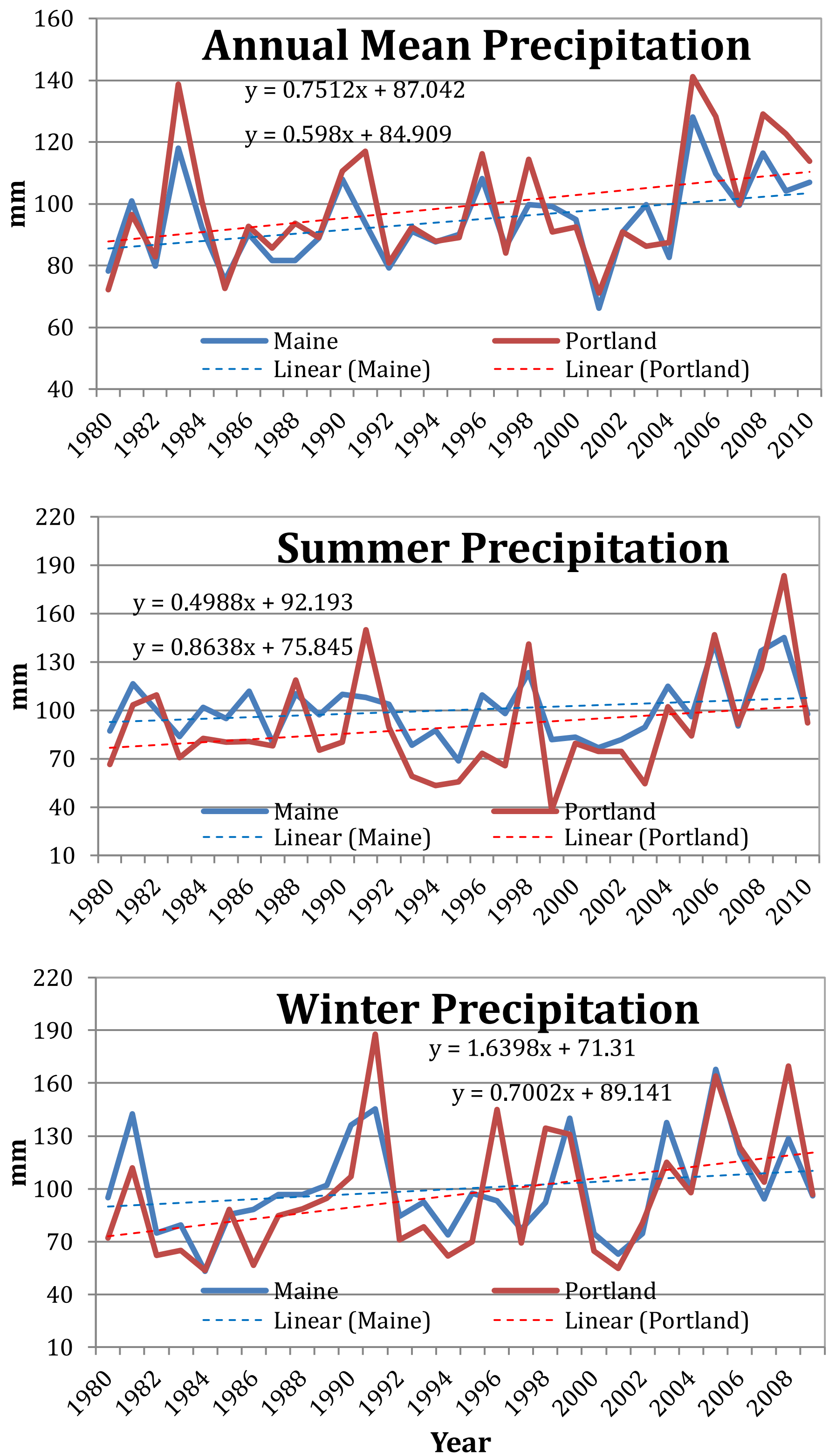

FIGURE 15 Observed Annual Variability of 30-year Annual Mean Precipitation, Summer Precipitation, and Winter Precipitation over Maine and the City of Portland

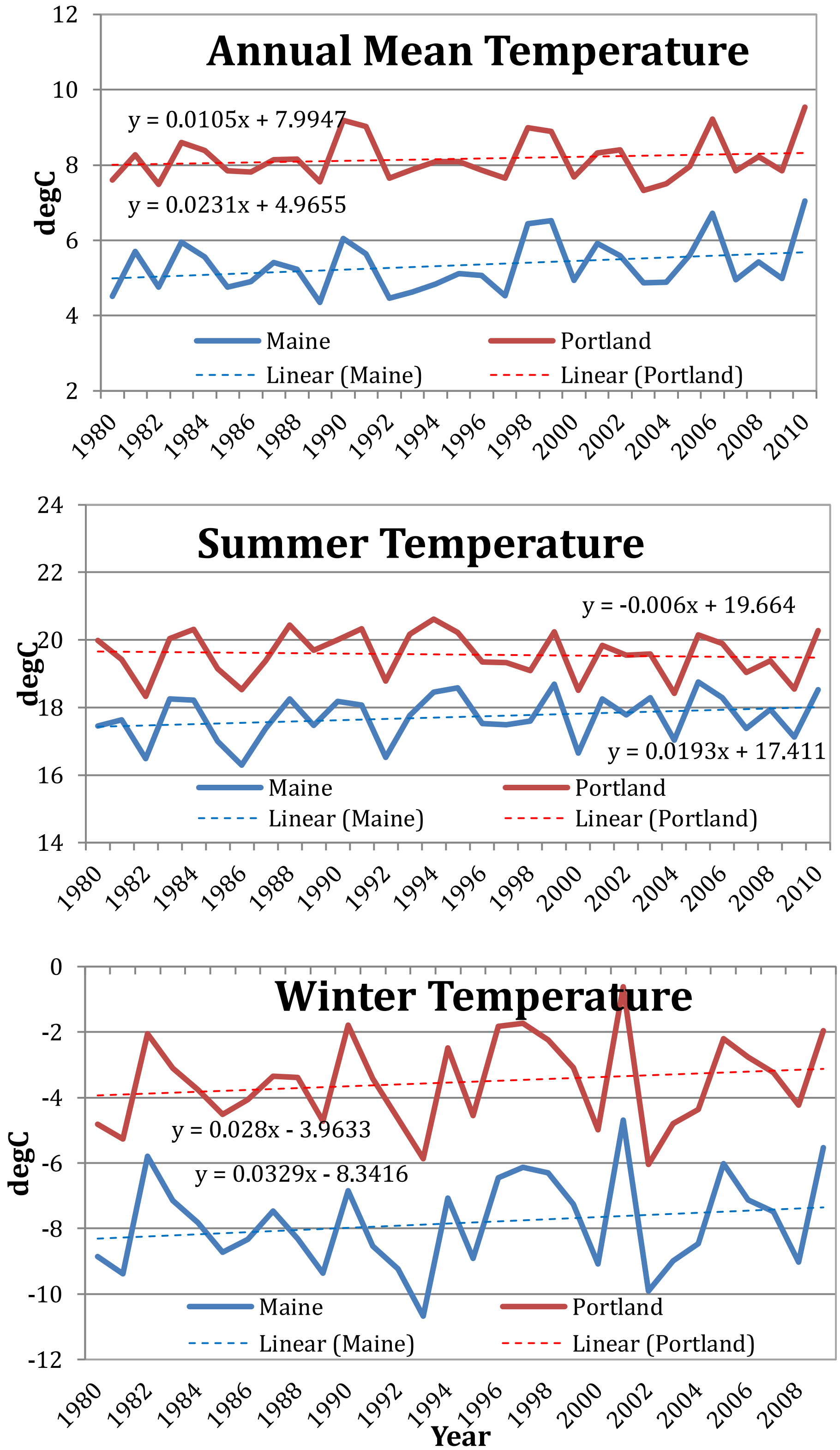

FIGURE 16 Observed Annual Variability of 30-year Annual Mean Temperature, Summer Temperature, and Winter Temperature over Maine and the City of Portland

5 CLIMATE MODELS AND MAINE

In order to understand the model projections and put them in context for decision making, it is critical to evaluate the performance of models in predicting the recent observational record. Here we discuss the model biases from global- and regional-scale models, and then we discuss projected changes for Maine based on these models for the middle of the century and the end of the century.

5.1 GCM MODELS AND THEIR BIAS FOR MAINE BASED ON HISTORICAL DATA (1980–2010)

Figure 17 shows the bias in surface temperature of GCMs when compared to the observational record from 1980 to 2010. We have compared two GCMs. One of the GCMs is the Community Climate System Model, version 4 (CCSM4), developed by the National Center for Atmospheric Research, United States (Gent et al. 2011). The spatial resolution of CCSM4 is 1.25 × 0.94 in longitude and latitude, respectively. The other GCM is the Geophysical Fluid Dynamics Laboratory Earth System Model with Generalized Ocean Layer Dynamics component (GFDL-ESM2G) developed by NOAA/Geophysical Fluid Dynamics Laboratory, United States (Donner et al. 2011). The spatial resolution of GFDL-ESM2G is 2.5 × 2.0 in longitude and latitude, respectively. There are about 9 grid points for CCSM4 and fewer than 4 grid points for GFDL over the state of Maine. In general, the CCSM4 overestimates both winter and summer temperature, while GFDL underestimates them.

A similar analysis showing the calculated bias in precipitation of two GCMs—CCSM4 and GFDL—is shown in Figure 18. In both winter and summer, the bias of CCSM4 is around 4 mm/day and the GFDL shows larger bias (wet bias).

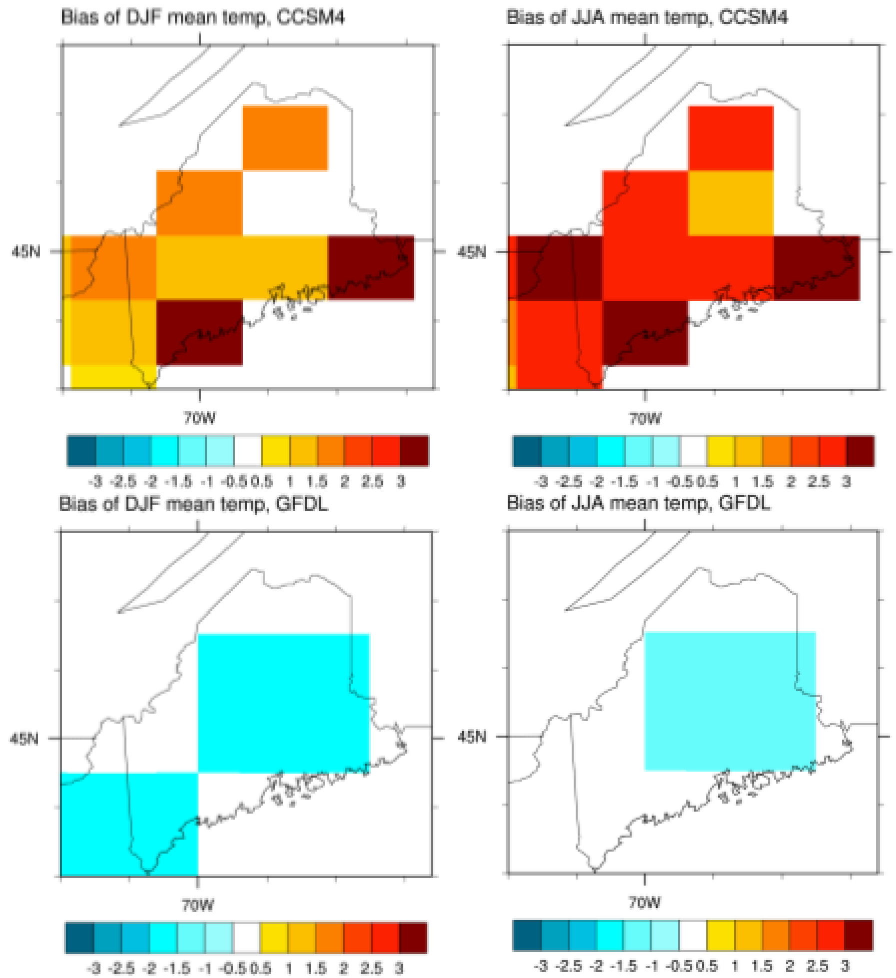

FIGURE 17 Calculated Bias of Global-model-simulated Surface Temperature (°C) (The figures on the left show the average for winter months [DJF: December, January, and February] and the right show the average for summer months [JJA: June, July, and August]. The top panels present the results from the CCSM4 model and the bottom panels present those from the GFDL model.)

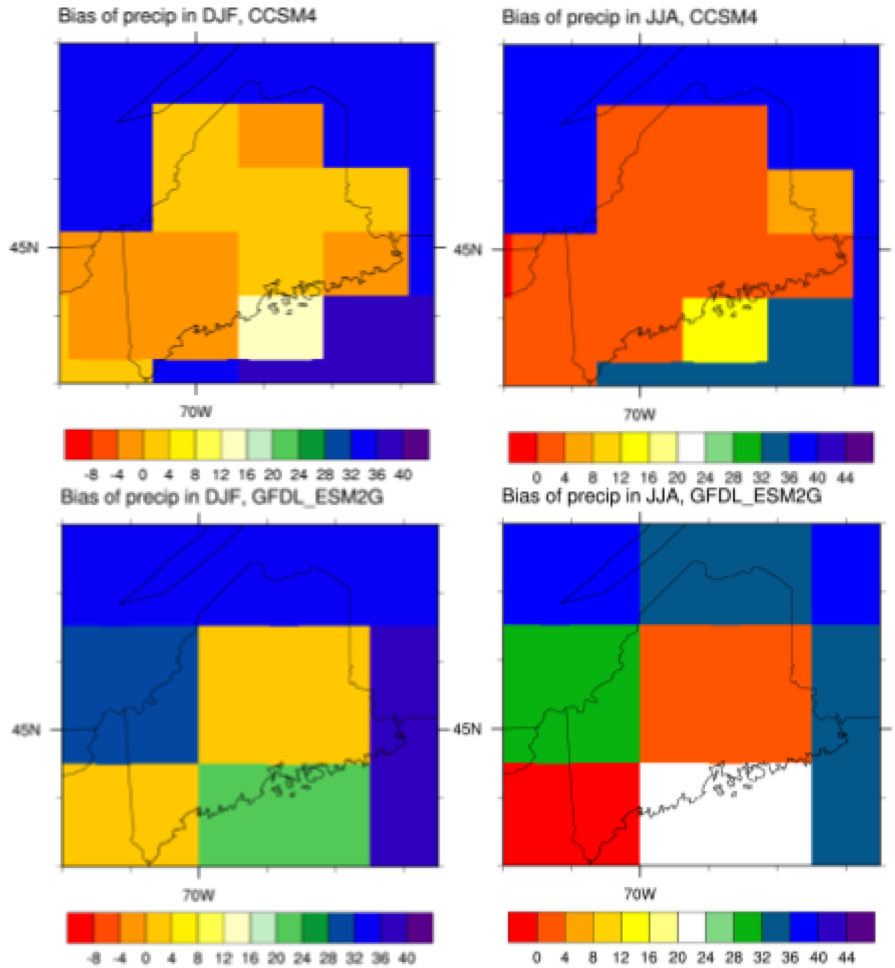

FIGURE 18 Calculated Bias of Global-model-simulated Daily Average Precipitation (mm/day) (The figures on the left show the average for winter months [DJF: December, January, and February] and the right show the average for summer months [JJA: June, July, and August]. The top panels present the results from the CCSM4 model and the bottom panels present those from the GFDL model.)

5.2 PROJECTED CHANGES FROM GLOBAL MODELS FOR THE REST OF THE CENTURY FOR MAINE

Figure 19 shows changes in temperature in the summer and winter as projected by the CCSM4 and GFDL models. Generally, both models project a warming in the mid-21st century under RCP8.5. In addition, both models project a weaker warming in summer and a stronger warming in winter. However, the GFDL model projects a stronger warming in winter than CCSM4 does.

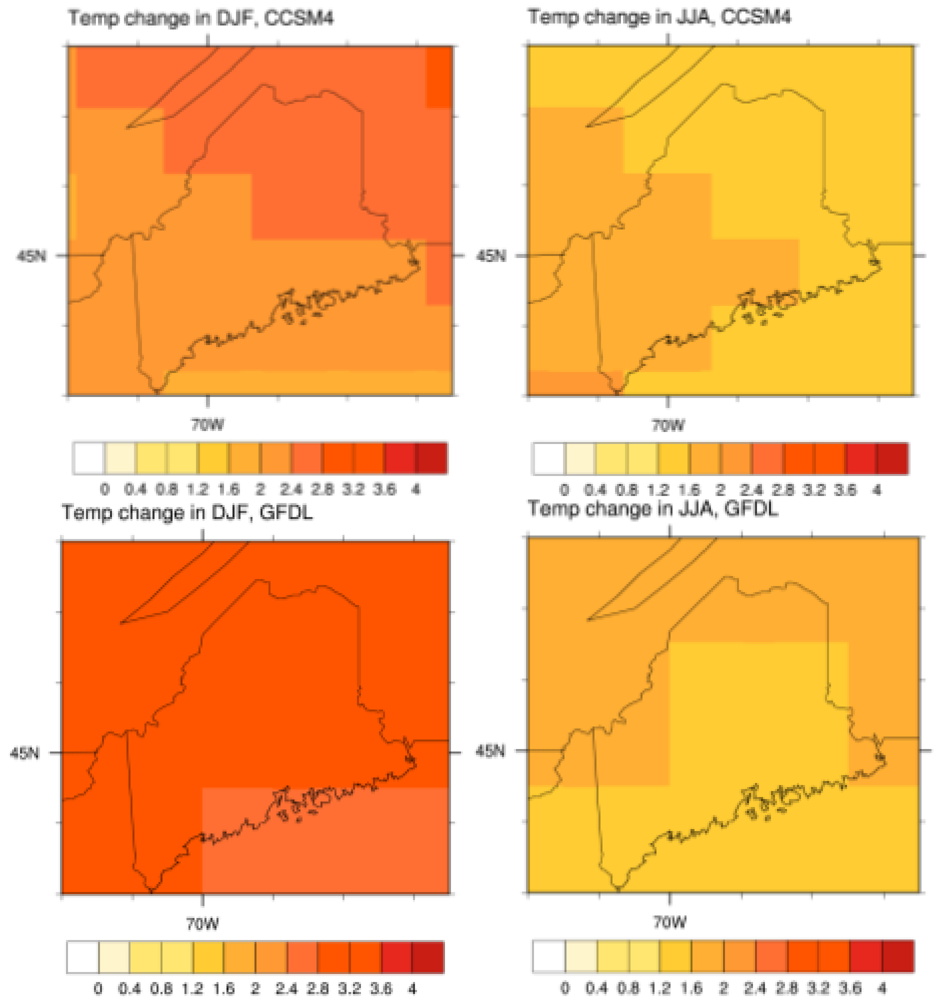

FIGURE 19 Global-model-projected Temperature (°C) Change in Summer (right) and Winter (left) of mid-21st Century (2045–2054) under RCP8.5 (The top panels show results from CCSM4, and the bottom panels show results from the GFDL model.)

Figure 20 shows the change in precipitation in winter and summer, as projected by CCSM4 and GFDL. CCSM4 projects a strong increase of precipitation (30–40%) by the mid-21st century under RCP8.5. However, the GFDL model projects a very weak change in winter precipitation. Both models show weak changes in summer precipitation.

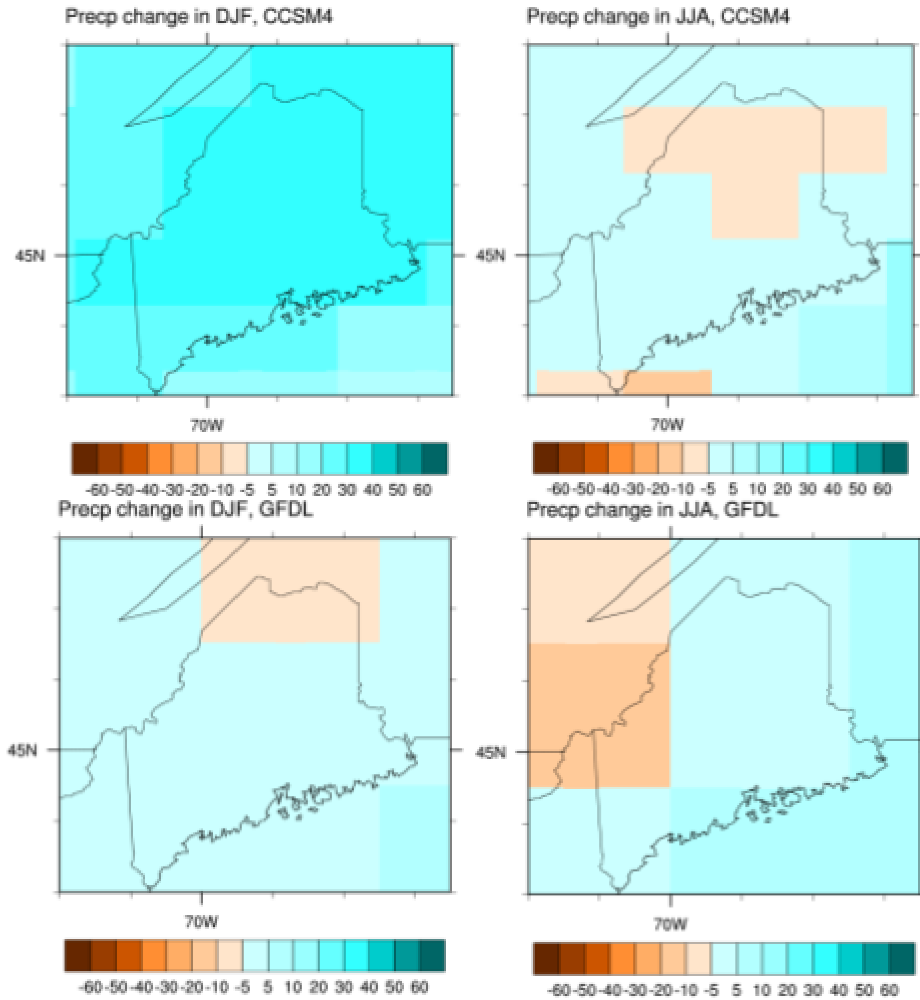

FIGURE 20 Global-model-projected Daily Average Precipitation (mm/day) Change in Summer (right) and Winter (left) of mid-21st Century (2045–2054) under RCP8.5 (The top panels show results from CCSM4, and the bottom panels show results from the GFDL model.)

5.3 HISTORICAL PROJECTIONS OF MAINE CLIMATE USING REGIONAL SCALE MODEL

We investigated four sets of dynamical downscaling results from the WRF model. Two sets of the downscaling apply CCSM4 model output as boundary conditions (labelled WRF_CCSM4), and the other two sets of downscaling apply GFDL model output as boundary conditions (labelled as WRF_GFDL). The model results shown here are performed with spectral nudging and bias correction of the input fields obtained from the CCSM4 model. This process is explained in Wang and Kotamarthi (2015). Figure 21 compares the bias in temperature as simulated by WRF_CCSM4. The WRF driven by bias-corrected CCSM4 shows less bias than those obtained from the GCM (Figure 17; top panel) for both summer (across all of Maine) and winter (southern half of Maine) temperature.

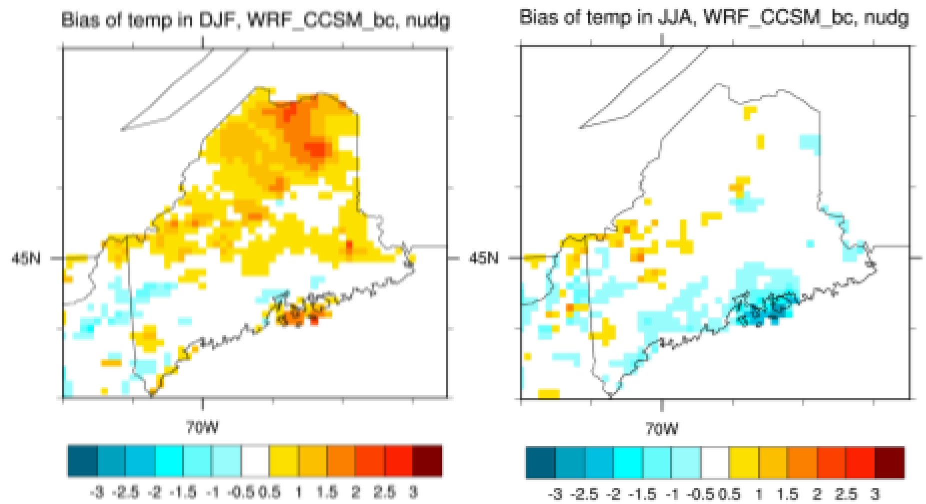

FIGURE 21 Bias of WRF-simulated Temperature (°C) in Winter (DJF: December, January, and February) and Summer (JJA: June, July, and August), Driven by Bias-corrected CCSM4 Model

Figure 22 shows bias in precipitation simulated by WRF, driven with bias-corrected CCSM4. The bias in summer precipitation is reduced when the boundary condition is bias corrected compared to GCMs (Figure 17).

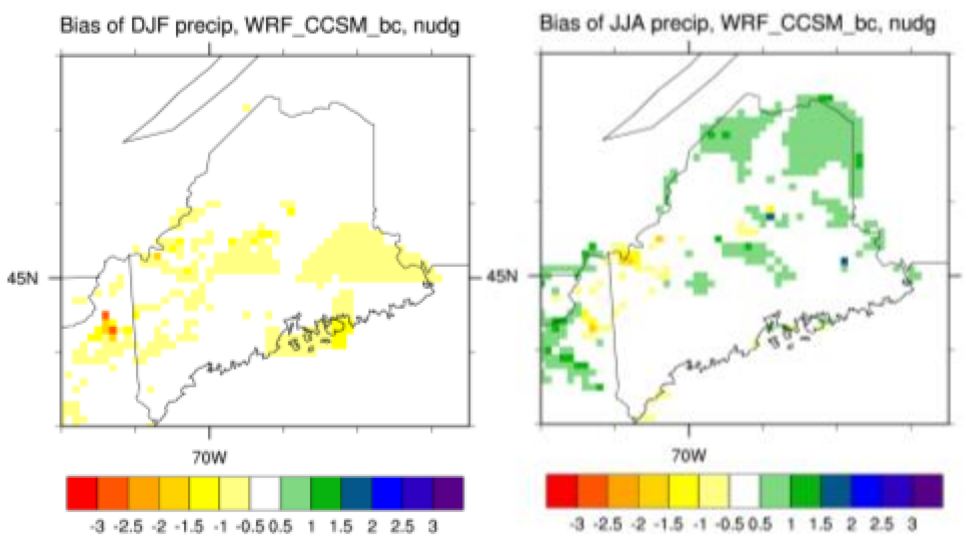

FIGURE 22 Bias of WRF-simulated Daily Average Precipitation (mm/day) in Winter (DJF: December, January, and February) and Summer (JJA: June, July, and August), Driven by Bias-corrected CCSM4 Model

5.4 PROJECTIONS FOR CLIMATE CHANGE FROM REGIONAL CLIMATE SIMULATIONS FOR MAINE

Figure 23 shows the temperature change in 2045-2054 projected by WRF_CCSM4 and WRF_GFDL. Similar to Figure 19, which shows the temperature changes projected by GCMs, both models project positive temperature changes in both summer and winter. In addition, they both project lower warming in summer and higher warming in winter. However, the WRF_GFDL model projects higher winter temperature change than WRF_CCSM4. The projected summer temperature change (1.2-1.6 °C [~2.16-2.88 °F]) is similar for WRF_GFDL and WRF_CCSM4.

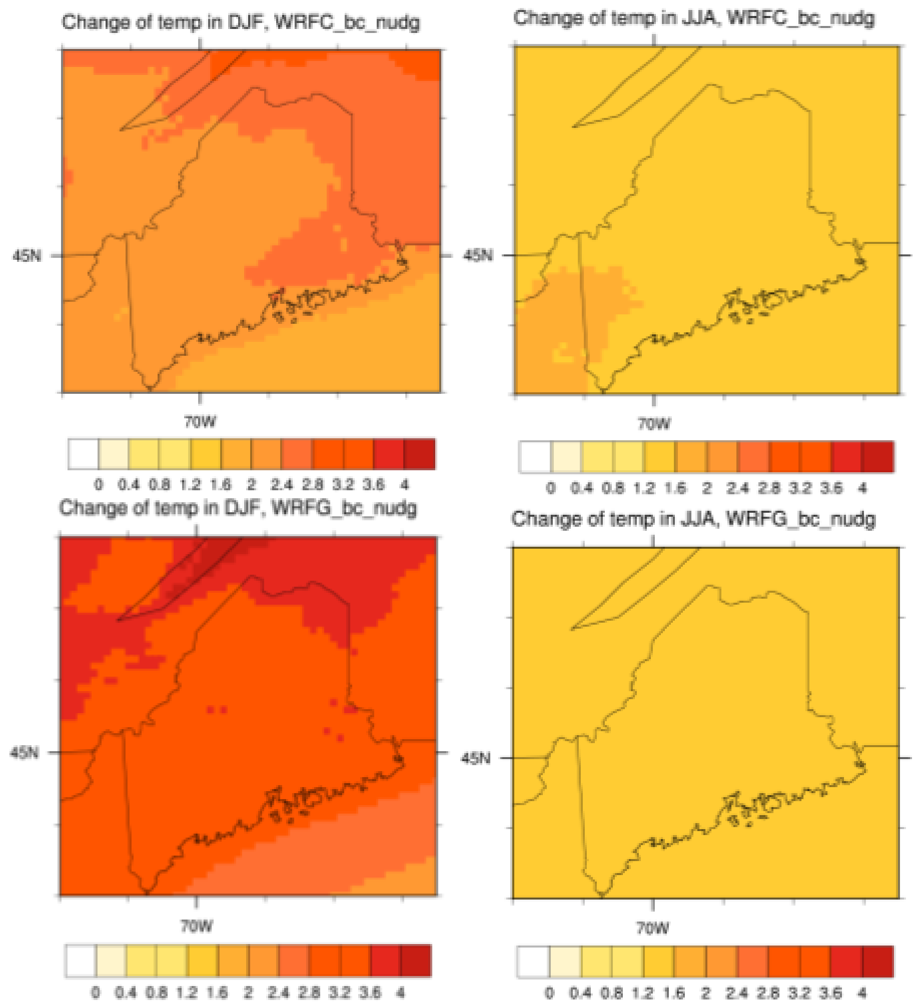

FIGURE 23 WRF-model-projected Temperature (°C) Change in 2045–2054 under RCP8.5 versus 1995-2004 (Top panels: WRF_CCSM4; bottom panels: WRF_GFDL. Both simulations apply bias correction and spectral nudging. The left panels are for winter months [DJF: December, January, and February] and the right panels are for summer months [JJA: June, July, and August].)

Figure 24 shows the WRF-projected precipitation change in 2045–2054 under RCP8.5. Both WRF_CCSM4 and WRF_GFDL project an increase in winter precipitation. The WRF_CCSM4 projects a much larger winter precpitation increase. The projected change in summer precipitation is small, although the WRF_GFDL projects a decrease in precipitation.

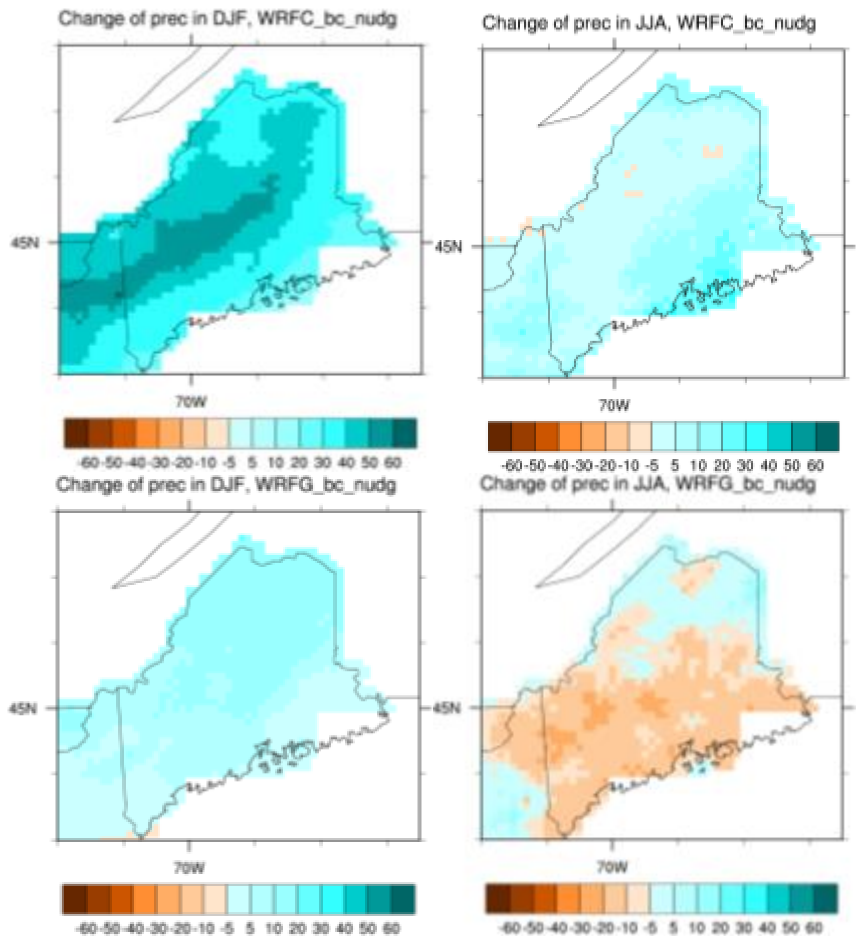

FIGURE 24 WRF-model-projected Daily Average Precipitation (mm/day) Change in 2045–2054 under RCP8.5 versus 1995–2004 (Top panels: WRF_CCSM4; bottom panels: WRF_GFDL. Both simulations apply bias correction and spectral nudging. The left panels are for winter months [DJF: December, January, and February] and the right panels are for summer months [JJA: June, July, and August].)

6 APPROACHES/RECOMMENDATIONS FOR USING CLIMATE MODELING PRODUCTS FOR ASSESSMENTS

Climate change assessments often require inputs from climate models; these inputs depend on the sector, depth of analysis, and expected outcomes of the assessment. A commonly followed path is to begin by performing a scenario analysis (Figure 2), followed by a more in-depth IAV analysis (Figure 3) based on the outcome of the scenario analysis. The data requirements for each stage of this process can be met by using readily available climate model outputs. The goal of scenario analysis is to survey a wide range of possible model outcomes based on GHG forcing scenarios. Coarse-spatial-resolution GCM output is often converted to high-spatial-resolution statistical downscaling products using numerous techniques available in the literature. Several of these model products are available freely (see Kotamarthi et al. [2016] for details on various statistical downscaling techniques and the availability of downscaled data they produce). As discussed earlier in this report and Kotamarthi et al. (2016), there are different levels of data needs depending on the complexity of the analysis. For example, Kotamarthi et al. (2016) state that there may be several instances where there is no need for quantitative climate data beyond description, such as "it will be warmer and wetter over a region." This may be sufficient information for making decisions on adapting to increased heat stress. The following is extracted from Kotamarthi et al. (2016) to illustrate the need for climate data products and the level of data that is necessary for various types of impact assessments:

> *The response of the public health department might be similar regardless of the exact numbers attached to the future projections: establish cooling centers, educate the public, and reduce the amount of highly absorptive land cover that exacerbates extreme heat conditions. In addition, even if clear trends in climate are not observed, exploring a system's resilience to current conditions can be informative. Frequently, human systems are not well adapted to current climate and weather hazards, let alone to projected future increases. The infrastructure destruction in New York and New Jersey in 2013 due to Hurricane Sandy is a case in point.*

As discussed in Section 3, the analysis paths for other applications may require more detailed climate data. This additional data is often comes the form of high-spatial-resolution model output developed using the processes described in Section 3.2.5. Again quoting from Kotamarthi et al. (2016),

> *Temperature and precipitation extremes often fall into this category, in which science is able to generate information through a combination of global modeling and downscaling and the agency or system requires such information to make robust decisions. Examples might include storm-sewer pipe diameter, where the cost of installation depends on the frequency of future heavy precipitation; rail transportation lines, where the choice of best material depends on the range of temperature extremes expected over the duration of the installation; or sea-level rise, where protection of coastal infrastructure may depend on both the amount of rise expected over a given time horizon and the risk of storm surge.*

Quantitative projections of climate change are used as input to other sector models for additional quantitative projections of sectoral impacts, for example:

- Water/Waste Water Impact Assessments: Calculations of streamflow, floods, and groundwater levels using hydrological models of varying complexity. Often the demand for quantitative climate model inputs depends on the hydrological model being used. The more physically based and higher resolution the hydrological model, the greater the demand for climate model inputs with higher spatial and temporal resolution.

- Infrastructure Risk and Integrity Assessments: Models of infrastructure risk and damage due to changes in frequency of extreme events and their strength using damage models/fragility curves requires climate information that these models convert into risk of design exceedance and development of adaptation plans.

- Agriculture: Assessing the impact of climate change on agriculture requires quantitative climate projections to estimate crop yield changes and potential changes in the availability of water and nutrients across a region and facilitate development of adaptation plans.

- Model of Energy Use and Demand: Models of energy use and demand forecasts by the various sectors of the economy are used to estimate the changes in use and demand in the future due to climate change (Franco et al., 2006; Isaac and van Vuuran, 2009; Jalcom et al., 2014; Swan and Ugursal, 2009). These energy sector models use a number of heating and cooling days and their changes in number in future decades to develop quantitative forecasts for energy use and demand.

- National Security Assessments: Changes in the demand for water, food, and energy are key considerations for national security assessments. Quantitative climate data could help international security assessments to identify future security risks and regions that are susceptible to strife.

In these cases, it is usually possible to use quantitative projections as input to calculate projected changes and their associated uncertainty over the next century. We will discuss the data needs and availability of data for in-depth IAV analysis, as shown in Figure 3, in the reminder of this document.

One of the critical needs for an in-depth IAV analysis of the climate change impacts on a particular sector is identifying and obtaining climate data (both observational and model) at the required frequency and spatial resolution. Although this process is best performed with the assistance of a climate scientist, it is possible to develop some general guidelines for the type of data available and its suitability for a particular IAV analysis task. Table 1 lists the three common modes of climate model output that is available to a user interested in performing in-depth IAV analysis of sectoral impacts as described in Section 2. Climate models operating at global scales are the original sources of climate data. The two different downscaling methods, statistical and dynamic, add additional spatial and time resolution, respectively, to the GCM output. GCM model simulations span from pre-industrial times (~1850s) to 2100 and beyond. To make these long simulations feasible, the models operate at a coarse spatial resolution; for many variables of interest to the IAV analysis community, they save model output as daily averages and maximum and minimum values. The number of GHG scenarios, as described by the RCPs, is also limited due to the computational complexity of the GCM and availability of computational resources. These simulations generally employ three to four different scenarios that span the range of the 70 available RCP scenarios.

The downscaling methods use GCM output to generate spatially disaggregated variable mapping, and hence are limited by the available GCM output. In addition, the dynamic downscaling is often as expensive as—or sometimes more computationally expensive than—running the GCMs using coarser resolution, which further limits the output available from dynamic downscaling. Statistical downscaling is often computationally inexpensive and hence is used to generate a wide variety of RCP scenarios over a range of spatial resolutions.

The choice of which output to use for an application depends on a number of factors. Some of these are set by the data needs for the in-depth IAV analysis. When several choices are available, often the availability of resources and project time constraints may dictate the choice of dataset for a particular IAV analysis. The next constraint is likely the familiarity of the team with traditional data formats, and analytical and visualization tools common to the climate modeling community. Most climate model output that uses both regional climate models and GCMs is in netcdf format. A number of freely available software programs can extract variables from these data files, manipulate the output, and visualize. The complexity of this task and the resources that may be needed to run these models and use model-generated output is listed in Table 2.

Table 3 summarizes recommendations on available model output that could be used for each of the lifeline sectors discussed in Section 2, and for three types of analysis of increasing complexity. The table should be used as a starting point for evaluating the data needs for the project; best practice would be to work with a climate scientist familiar with all these data products to further down-select the data options before embarking on the IAV analysis. Many of these model products are continuously upgraded and recomputed to make use of recent model developments, achieve higher spatial resolutions, and increase the ensemble size. Thus, the recommendations need to be evaluated often in the light of new data availability.

TABLE 1 Commonly Available Model Outputs, Variables, and Data Format and Their Availability for Performing Impact Assessments

Model Type	Variables	Spatial Resolution	Time Resolution	Format Available	GHG Scenarios	Availability
GCM	Daily average surface temperature, daily minimum temperature, daily maximum temperature, daily average precipitation, solar flux, relative humidity, monthly and seasonal averages of temperature, precipitation	Depends on the model and ranges from 300 km × 300 km grid cell to 100 km × 100 km	Daily average, monthly average, and annual averages	netcdf formatted files	RCP 8.5, RCP 4.5, RCP 2.6, RCP 6.0	CMIP5 Repository
Statistical Downscaling	Surface temperature precipitation, solar input and relative humidity	Can be produced to fit the required resolution (range between 50 km × 50 km and 1 km × 1 km)	Daily mean, monthly, seasonal, and annual averages	CSV tables and text files	All available GCM output scenarios	Various sources[a]
Dynamic Downscaling	Surface temperature, precipitation, relative humidity, solar input, wind fields, surface pressure and several other variables of interest; variables available range from 20 to 100, depending on the model	Spatial resolution of the output varies between 12 km × 12 km to 50 km × 50 km	Output is available every few hours (every 3 hours), to daily averages	netcdf files	Limited to a few GHG scenarios	Various sources[b]

[a] Statistical downscaling products are available from the U.S. Geological Survey and from the National Aeronautics and Space Agency (see Kotamarthi et al. [2016] for more information).

[b] Dynamic downscaling data sources include North American Regional Climate Change Assessment Program (NARCCAP) (50-km resolution), Coordinated Regional Climate Downscaling Experiment (CORDEX) (ongoing activity), and Argonne National Laboratory.

TABLE 2 Selection Matrix for Climate Model Output for Selected Variables, Availability, Matched with the Expertise Level of the User and Computational Needs (colors indicate the level of difficulty for each task: dark green = easy, light green = moderate, and orange = difficult)

Accessibility		
	Data formats	Ease of use
GCM	Experienced User (netcdf)	Experienced User
SD	Novice User	Novice User
RCM	Experienced User	Experienced User

Temperature		
	Monthly, annual means	Ease of computing
GCM	Yes	Medium
SD	Yes	Novice User
RCM	Yes	Medium

Temperature		
	Complexity	Resources
GCM	Experienced Modeler	Multi member team; HPC computing
SD	Some Expertise	Modest computing
RCM	Experienced Modeler	Modest computing

Producing Data		
	Extremes	Ease of computing
GCM	Yes (large regional scales)	Medium
SD	No	No
RCM	Yes (regional and local)	Medium

Precipitation		
	Monthly, annual means	Ease of computing
GCM	Yes (large regional scales	Medium
SD	Yes	Novice User
RCM	Yes (regional and local)	Medium

Precipitation		
	Extremes	Ease of computing
GCM	Yes (large regional scales)	Medium
SD	No	No
RCM	Yes (regional and local)	Medium

TABLE 3 Recommendation on Using Climate Model Products for Selected Sectoral Impact Analysis

Sector	Analysis Level	General Climate Data Needs	Climate Variable Needs	Recommended Climate Data
Hydrology and Hydrological Assessments	Scenario	Large number of GHG scenarios, coarse resolution and seasonal to annual means	Monthly and seasonal averages of temperature and precipitation	GCM output from CMIP5 and statistical downscaling output
	In-depth IAV analysis	Selected number of GHG scenarios, high spatial and time resolution	High spatial resolution diurnal temperature and precipitation	Statistical downscaling and dynamic downscaling model outputs
	Extreme events impacts	Selected number of GHG scenarios, high spatial and time resolution and extreme events data and statistics	High spatial and time resolved data for identifying extremes	Dynamic downscaling model outputs are the most likely candidates; some statistical downscaling methods also produce statistics of extremes[a]
Energy	Scenario analysis	Large number of GHG scenarios, coarse resolution	Monthly and seasonal averages of temperature and relative humidity, number of heating days, cooling days	GCM output from CMIP5 and statistical downscaling output
	In-depth IAV analysis	Selected number of GHG scenarios, high spatial and time resolution	High spatial resolution diurnal temperature, relative humidity, number of days with temperature over and below a threshold for estimating heating and cooling demand	Statistical downscaling and dynamic downscaling model outputs
	Extreme event analysis	Selected number of GHG scenarios, high spatial and time resolution and extreme events data and statistics	High spatial and time resolved data for identifying extremes in temperature as a consecutive number of days above a threshold or below a threshold; ice storm events and hurricanes	Dynamic downscaling model outputs are the most likely candidates; statistical downscaling methods also produce these statistics; ice storm possibilities can likely be estimated from data saved in dynamically downscaled output and projections of hurricanes are uncertain.

TABLE 3 (Cont.)

Sector	Analysis Level	General Climate Data Needs	Climate Variable Needs	Recommended Climate Data
Transportation Sector	Scenario analysis	Large number of GHG scenarios, coarse resolution.	Monthly and seasonal averages of temperature, precipitation	GCM output from CMIP5 and statistical downscaling output
	In-depth IAV analysis	Selected number of GHG scenarios, high spatial and time resolution	High spatial resolution diurnal temperature, relative humidity, precipitation; estimates of number of days with precipitation vs dry days; estimates of precipitation as snow and amounts.	Statistical downscaling can provide some of the inputs and dynamic downscaling model can provide most of these variables.
	Extreme event analysis	Selected number of GHG scenarios, high spatial and time resolution and extreme events data and statistics	High spatial and time resolved data for identifying extremes in temperature as a consecutive number of days above a threshold or below a threshold; high precipitation events and number of wet days; precipitation that is snow and ice.	Dynamic downscaling model outputs are the most likely candidates; statistical downscaling methods also produce these statistics; ice storm possibilities can likely be estimated from data saved in dynamically downscaled output

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