

SERDP REPORT

USE OF CLIMATE INFORMATION FOR DECISION- MAKING AND IMPACTS RESEARCH: STATE OF OUR UNDERSTANDING

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CONTENTS

ACKNOWLEDGEMENTS	viii
ACRONYMS AND ABBREVIATIONS	ix
EXECUTIVE SUMMARY	1
1 THE CHANGING CLIMATE.....	3
1.1 Regional Climate Changes in the United States	3
1.2 Climate Change and Spatial Scales.....	4
1.3 Goals and Content of This Document.....	6
1.4 Climate Change Information Use in Vulnerability and Impact Assessments.....	7
2 THE BASIS FOR FUTURE PROJECTIONS	10
2.1 What Type of Climate Information Is Really Needed?	10
2.2 Future Emission and Concentration Scenarios	12
2.3 Global Climate Models	12
2.4 Uncertainty	14
3 INTRODUCTION TO DOWNSCALING	17
3.1 Dynamical Downscaling.....	18
3.2 Empirical Statistical Downscaling.....	19
3.3 Comparison of Dynamical and Statistical Downscaling methods	21
4 RECOMMENDATIONS/GUIDELINES	28
4.1 Recommended Approach.....	30
4.2 Illustrative Examples of Impact Areas Important to the U.S. Department of Defense	30
4.2.1 Human Health	30
4.2.2 Hydrology	32
4.2.3 Ecology	32
4.2.4 Built Infrastructure	32
4.2.5 Available Climate Data for DoD Needs and Their Limitations	33
4.3 Regional Descriptions of Climate and Climate Modeling Considerations	34
4.3.1 Technical Terminology in Reference to Regional Climate Descriptions	36
4.3.2 Southwest, Including Coastal Southern California.....	38
4.3.3 Great Plains	39
4.3.4 Midwest.....	39
4.3.5 Northeast	40

CONTENTS (Cont.)

4.3.6	Southeast and Gulf Coast.....	41
4.3.7	Mountain West.....	42
4.3.8	Northwest/Pacific Coast.....	42
4.3.9	Pacific Islands Region.....	43
4.3.9.1	Hawaiian Islands and Midway Islands	43
4.3.9.2	Northern Mariana Islands and Guam.....	44
4.3.9.3	Marshall Islands, Micronesia	44
4.3.9.4	American Samoa, South Pacific	44
4.3.10	Puerto Rico, Guantanamo Bay, and U.S. Virgin Islands	45
4.3.11	Alaska	45
5	REFERENCES	47

FIGURES

1	Spatial Scale of Global Models, Regional Models, and Impact Assessments.....	5
2	Interactions between the Climate and Socioeconomic Processes That Lead to Determination of Vulnerability, Exposure, and Risk.....	7
3	Results of a Stress Test for the Colorado Spring Water System.....	9
4	Projected Changes in U.S. Annual Mean Temperature	13
5	Relative Importance of Different Sources of Uncertainty in Future Climate Projections over Time	16
6	Typical Set of Processes and Spatial Scales Modeled by a Regional-Scale Climate Model	19
7	Scales of Atmospheric Motion in Reference to Meteorological Phenomena.	34

TABLES

1	Summary of Widely Used Statistical Downscaling Methods, an Example of Each Method, and Characteristics of Available Outputs.....	22
3	Evaluation of Available Downscaling Models and Output and Their Limitations	31
4	Recommendation Table on the Use of Climate Datasets based on Regional Features	36

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ACRONYMS AND ABBREVIATIONS

BCSD	Bias Correction/Spatial Disaggregation
CDFT	Cumulative Distribution Function Transform
CMIP3	Coupled Model Intercomparison Project Phase 3
CMIP5	Coupled Model Intercomparison Project Phase 5
CMIP6	Coupled Model Intercomparison Project Phase 6
CONUS	Contiguous United States (encompassing the lower 48 states)
DoD	Department of Defense
EBM	Empirically Based Method
ESDM	Empirical Statistical Downscaling Method or Model
EDQM	Equidistance Quantile Mapping
EF	Enhanced Fujita Scale
ENSO	El Niño Southern Oscillation
ESM	Earth System Model
GCM	Global Climate Model (or General Circulation Model, when referring to the older climate models that consisted of atmospheric and ocean components only)
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Inter-Tropical Convergence Zone
KDDM	Kernel Density Distribution Mapping
MBC	Monthly Bias Correction
NA-CORDEX	North American Coordinated Regional Downscaling Experiment
NARCCAP	North American Regional Climate Change Assessment Program
NASA	National Aeronautics and Space Administration
NBC	Nested Bias Correction
NCDC	National Climate Data Center
NCEP	National Centers for Environmental Prediction.
NOAA	National Oceanic and Atmospheric Administration
q-q	Quantile-Quantile
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
SDSM	Statistical Downscaling Model
SERDP	Strategic Environmental Research and Development Program
SRES	Special Report on Emissions Scenarios

SREX	Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation
USGS	U.S. Geological Survey
WBGT	Wet Bulb Globe Temperature

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EXECUTIVE SUMMARY

Much of human society and its infrastructure has been designed and built on a key assumption: that future climate conditions at any given location—including average temperature, precipitation, sea level, and the frequency and intensity of extreme events—will be similar to those experienced in the past. This assumption affects infrastructure design and maintenance, emergency response management, and long-term investment and planning. As evidence accumulates that climate change already is affecting human society and the built environment, however, this assumption has become less and less tenable.

The Department of Defense (DoD) is responsible for vast amounts of built and natural infrastructure at its permanent installations and other sites. This infrastructure is necessary for maintaining military readiness and supporting daily operations, and it is subject to requirements related to basic tenets of asset stewardship. Given its worldwide presence, the different spatial and temporal scales upon which it bases its decisions, and its previous missions, DoD requires useful and actionable climate information over a range of scales to serve a variety of purposes. , However, the provisioning of actionable climate information to decision-makers and practitioners—especially at spatial scales relevant to decision-making—is in its infancy. Although a vast amount of climate information is available at different spatial scales and temporal resolutions, corresponding information on its utility and appropriateness of use in a decision-making context is lacking.

This primer on the appropriate use of climate information for non-experts was commissioned by the Strategic Environmental Research and Development Program (SERDP) as an outgrowth of a set of five funded research projects investigating decision-making in DoD and its relationship to available and needed climate information at appropriate spatial and temporal scales. Focusing on applications to vulnerability and impact assessments and adaptation planning, it provides information for selecting climate information and downscaled climate products. The information is presented at a level useful for action officers within the Office of the Secretary of Defense, military service headquarters, installation oversight commands, planners at different levels, and key installation managers who have a range of knowledge about and experience with climate change, climate modeling, and the application of climate information to built and natural infrastructure management planning, maintaining military readiness and installation-based operations, and other related types of decision-making.

The impacts research community, much of which has been funded by SERDP since 2009 in support of DoD climate-related research needs, also requires a better understanding of the use of high-resolution climate information. For that reason, this primer provides a summary of available climate information and a broad outline of the ways such information can be incorporated into vulnerability and impact assessments, climate resilience and preparedness considerations, and adaptation planning from a research perspective.

This document also includes a summary of the state of the science, our understanding of the appropriate use of that science in the context of decision-making, and a description of current

and future research topics that clearly explain why climate is changing, how climate projections are generated, what types of climate impacts are studied, and how the results can be used in further analyses to inform planning, general decision-making, and impacts research.

Because the most appropriate climate inputs for any given application depend on the nature of both risk tolerance and associated vulnerabilities, this is not intended as a prescriptive guidance document that outlines the “best” climate models, methods, or projections to use in any planning exercise. Instead, our goal is to convey a basic understanding of climate change, global climate models, and future scenarios to place the use of high-resolution climate information into an appropriate context. We then focus on the available downscaling methods used to generate high-resolution climate projections at the local to regional scale, with the goal of outlining our current understanding of their appropriate use (or non-use) in decision-making and impacts research. We also offer recommendations as to appropriate use of downscaled model output for some regions with specific geographic or terrain features that constrain viable choices.

The ultimate goal of this document is to help DoD users—and by extension those conducting the impacts research that informs potential decisions—to make useful decisions informed by the state of the science in a rapidly changing climate. We recognize, however, that this is just a first step. Moving forward, it is imperative that a closer and continuing dialogue occur between the climate modeling and user communities to advance our scientific understanding of the climate system in a manner that incorporates user needs into the design of scientific experiments, and that periodically provides users with updated guidance on how to apply credible climate information for decision-making purposes and impacts research.

1 THE CHANGING CLIMATE

Much of human society and its infrastructure has been designed and built on a key assumption: that future climate conditions at any given location—including average temperature, precipitation, sea level, and the frequency and intensity of extreme events—will be similar to those experienced in the past. In scientific and engineering terms, this assumption can be termed **stationarity**. This assumption underlies infrastructure design and maintenance, emergency response management, and long-term investment and planning, in which both past decisions and future plans rely on historical records of heat and cold, drought and flood, hurricanes and storm surges, or other aspects of long-term climate.

Today, however, this assumption of stationarity is becoming problematic. Increasing emissions of carbon dioxide, methane, and other heat-trapping **greenhouse gases** from human activities, primarily the burning of fossil fuels and changing land use, are building up in the atmosphere. In many areas, human-induced climate change is interacting with and exacerbating both new and existing patterns of natural variability and climate- and weather-related phenomena. Such phenomena range from rising seas and stronger storm surges along the coasts to more frequent heavy precipitation events across the midlatitudes to extreme heat inland. These and other consequences of human-induced climate change are expected to become even more widespread and pronounced over time, as the planet responds to past emissions and as more heat-trapping gases continue to build up in the atmosphere as a result of present and future human choices.

Stationarity and Climate Change

Stationarity signifies that statistics of climate conditions (e.g., temperature, precipitation) remain the same when averaged over a sufficiently long time period and that the future will be similar to the recent past. However, climate model projections and observations over the past few decades indicate that this is no longer the case, and that we will continue to experience non-stationarity as a result of human-induced climate change over the coming century and beyond. This change includes shifts in the means, variance, and distribution functions that we now use to represent climate conditions.

1.1 REGIONAL CLIMATE CHANGES IN THE UNITED STATES

The global climate is changing as a result of human emissions of heat-trapping gases. In the United States, annual and seasonal temperatures have increased by 1.3 to 1.9°F (0.7 to 1.1°C) since records began in 1895, with the greatest increases occurring since the 1970s (Walsh et al. 2015). (As temperatures have increased, the frost-free season has lengthened, and both extreme heat days and multi-day heatwaves have become more frequent and more intense.) Since long-term records in the state began in 1925, Alaskan temperatures have already warmed nearly twice as fast as those in the contiguous United States (CONUS); this disproportionate warming of the Arctic compared to midlatitudes is expected to continue in the future as the extent of sea ice and land-based ice and snow declines. Precipitation is also changing; as the atmosphere warms, more water evaporates from oceans, lakes, and rivers, increasing the average amount of precipitation associated with midlatitude storms, tropical storms, and even hurricanes. Higher levels of water vapor in the atmosphere have already increased the frequency of heavy rainfall and precipitation

events across much of the United States over the past 50 years, particularly in the Midwest and the Northeast.

Over the coming century, global average temperatures are projected to continue to increase at a rate of change that could exceed by a factor of 50 that experienced between the end of the last Glacial Maximum (commonly referred to as the last ice age) and the current warm interglacial period of today (Clark et al. 2016).

Projections of the Earth's future climate are calculated by global climate models (see Section 2.3). These models use a range of standard representative concentration pathways (RCPs) or Special Report on Emission Scenarios (SRES) scenarios as input, each of which corresponds to a specific pathway of carbon and other heat-trapping gas emissions or concentrations from human activities (see Section 2.2). For many regions, the magnitude and rate of change often depend on the scenario used, with higher emissions or concentrations corresponding to greater and/or more rapid change. In coming decades, for example, average temperature increases in the United States on the order of 2 to 4°F (1.1 to 2.2°C) are projected under lower to higher scenarios, respectively. By end of the century, temperature increases ranging from 5 to 10°F (2.8 to 5.6°C) are projected under lower to higher scenarios (Walsh et al. 2015). These future scenarios represent the largest uncertainty in projections of temperature toward the end of this century, emphasizing the role of human decisions in determining future change (see Section 2.4).

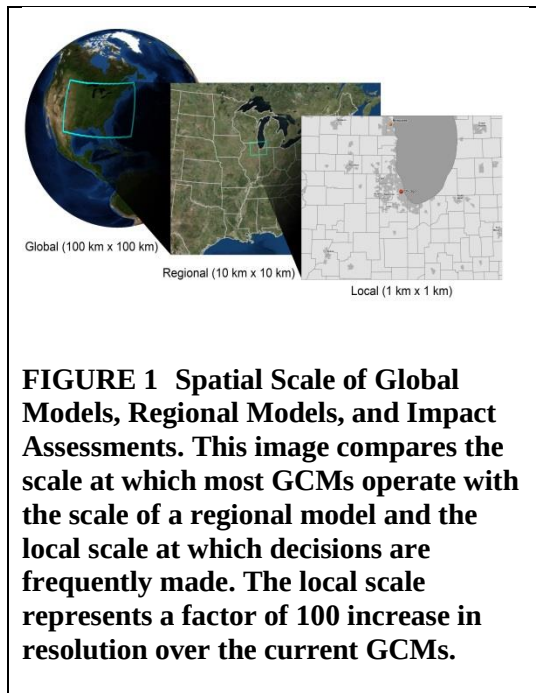
Climate change is also expected to affect precipitation and flood risks. Winter and spring precipitation will likely increase across Alaska and the northern half of North America, including the more northern CONUS states. Summer rainfall is likely to decrease (and summer drought risk is expected to increase) across the southern Great Plains and in the Southwest. Observed trends in the frequency of heavy rainfall and precipitation events are likely to continue, and as sea level rises (with global estimates ranging from 8 inches to 6.6 feet [0.2 to 2 meters] by 2100; Walsh et al. 2015) coastal flood risks will also increase.

1.2 CLIMATE CHANGE AND SPATIAL SCALES

Climate models—first known as general circulation models—were initially developed to model the energy budget of the earth system and the impact of external factors such as solar input and greenhouse gas emissions. Over the past two decades, these models have become progressively more complex. Now referred to as global climate models (GCMs), their capabilities have increased to incorporate more aspects of the dynamics, chemistry, and biology of the atmosphere, biosphere, and oceans.

GCMs divide the atmosphere, ocean, and land surface up into millions of discrete cells to solve numerical equations representing the physical, biological, and chemical phenomena in each, using state-of-the-art supercomputers. The model resolution (i.e., the size of the cells) has been progressively refined. Current GCMs operate at spatial resolutions of approximately 40 to 100 square miles (or 100 to 250 km²) per cell, as both historical data and future projections

indicate that regional- and local-scale changes in climate will frequently differ from continental-scale and global climate means (see Figure 1).



Most of the adaptation, impacts, and mitigation needs for the Department of Defense (DoD) and similar federal agencies are at scales much smaller than the resolution of even the latest GCMs. Instead, climate information at these smaller spatial and temporal scales can be obtained using downscaling methods. Downscaling climate projections introduces new information—either from observations (in the case of statistical downscaling) or from higher-resolution dynamical modeling (in the case of dynamical downscaling)—and combines this information with GCM output to generate higher-resolution information from coarser-resolution fields consisting of local weather and climate characteristics like temperature, humidity, and precipitation. For many applications, climate information from global and regional models must also be empirically *bias corrected* before the output can be used directly to quantify impacts. This

typically consists of using empirical data to identify and remove the offset in the absolute value of historical model output compared to observations, a process that is typically internalized in most statistical downscaling approaches.

Model Bias and Bias Correction Approaches

All dynamical climate models (both regional and global) aim to reproduce the observed climate system. While they do a good job, there remain errors or biases in the models. **Bias** refers to the difference between what the model simulates as the observed climate and the actual observed climate. In general, biases are determined on a variable basis (e.g., one determines the bias in surface temperature).

Bias Correction: In general these biases need to be removed to use the results of the global or regional models in impacts assessments. Removing the biases by correcting the climate model results based on observations is known as bias correction. A number of different approaches are used to do this, and these are described in the sections on statistical downscaling.

1.3 GOALS AND CONTENT OF THIS DOCUMENT

Given the magnitude and rate of present-day and future climate change, it is becoming increasingly relevant for action officers, planners, and managers to incorporate climate information into long-term planning. “Account for climate change in future planning” is more easily said than done, however. A great deal of information is available, ranging from historical observations to future projections. For some applications, it may seem that too much input must be incorporated to be practical; for others, it may seem that none of the available resources meet known needs.

This document attempts to identify appropriate climate data and climate information for vulnerability and impact assessments and impacts-related research. The Strategic Environmental Research and Development Program (SERDP) commissioned this primer on the most appropriate use of climate information by non-experts as an outgrowth of five funded research projects investigating decision-making in the DoD and its relationship to available and needed climate information at appropriate spatial and temporal scales. In it, we describe appropriate uses of high-resolution climate information, including when *not* to use such information. We also summarize available future climate information and outline how such information can be incorporated into vulnerability and impact assessment, climate resilience and preparedness considerations, and adaptation planning.

Because the most appropriate climate inputs for any given application depend on the nature of both risks and vulnerabilities, this is not intended to be a guidance document that identifies the “best” climate projections to use in any planning exercise. Instead, our goal is to convey a basic understanding of climate change, global models, future scenarios, and the downscaling methods used to generate high-resolution climate projections at local to regional scales, as well as the appropriate use of such methods based on our understanding of these approaches today. As scientific understanding progresses and the application of climate projections to impact assessment and decision-making becomes more advanced, this understanding should be updated to account for new approaches to modeling, downscaling, implementation, and interpretation of climate-related information.

Types of Climate Change Information Available for Decision Framing

- **Global-scale climate model evaluations organized by the World Climate Research Programme (WCRP):** This type of output is produced by GCMs. The most recent evaluations, CMIP3 and CMIP5, provide output from a large ensemble of different climate models, forcing conditions, and outputs for estimating likely climate change impacts at global, continental, and broad regional scales.
- **Regional-scale dynamic downscaling:** This type of output is produced using regional-scale climate models with information from GCMs applied at the boundaries. The North American Regional Climate Change Assessment Program (NARCCAP) database is one of the best-known examples of this type of information.
- **Empirical statistical downscaling methods or models (ESDMs):** This type of output is produced using statistical downscaling methods that combine information from GCMs and empirical observations. It encompasses a large variety of methods and datasets.

1.4 CLIMATE CHANGE INFORMATION USE IN VULNERABILITY AND IMPACT ASSESSMENTS

Vulnerability as adopted by the Intergovernmental Program on Climate Change (IPCC) (Fussler and Klein 2006) is best understood as an “integrated vulnerability of a particular system over a specified time horizon to anthropogenic climate change.” Vulnerability in the context of climate change is defined by the IPCC (Houghton et al. 2001) as the degree to which a system is susceptible to or unable to cope with adverse climate change, including climate variability and extremes. Thus, vulnerability assessments require knowledge of the character, magnitude, and rate of climate change to which a system is exposed; the system’s sensitivity; and the system’s adaptive capacity.

Vulnerability assessments include assessments of impacts from anthropogenic climate change, the effects of any mitigation action, and adaptation. Fussler and Klein (2006) further divide vulnerability assessments into two segments or “generations.” The first-generation vulnerability assessment includes impacts primarily from climate change, and the second-generation vulnerability assessment focuses on the adaptive capacity of the system and the impacts of additional non-climate drivers. In some cases, as noted in the box above, future uncertainty in these non-climate drivers may outweigh or even overwhelm the impacts of climate change on a given system.

To illustrate, Figure 2 shows a schematic of interactions that take place primarily between the climate and socioeconomic processes that lead to determination of vulnerability, exposure, and risk. This schema was used in both the IPCC Special Report on Extremes (SREX) (Field et al. 2012) on the effects of extreme weather and climate events and in the IPCC Working Group 2 Report (Birch et al.

Role of Climate Information in Complex Systems

The emerging **non-stationarity** of the climate baseline over multidecadal timescales relevant to human decision-making and infrastructure design poses a significant challenge for future planning. At the same time, however, it is important to recognize that the impacts of climate change on a complex system will be significantly modified by other factors—many of which may have nothing to do with climate, and some of which may mean that climate change is not the most important uncertainty in planning for the future of a given system or set of infrastructure. For example, studies such as Jones et al. (2015) have established that, by the mid-21st century, population distribution changes in the United States will be as important as likely climate changes in determining population exposure to extreme heat.

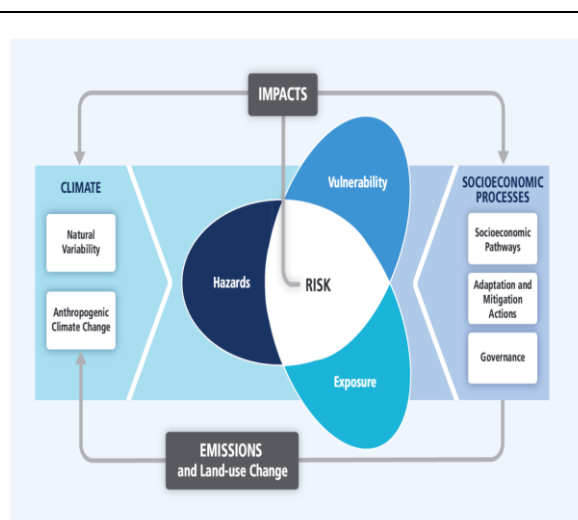


FIGURE 2 Interactions between the Climate and Socioeconomic Processes That Lead to Determination of Vulnerability, Exposure, and Risk (based on Oppenheimer et al. 2014, Chapter 19, Emergent Risks and Key Vulnerabilities, Figure 19-1)

2014) on impacts, adaptation, and vulnerability. Risk of climate-related impacts results from the interaction of climate-related hazards with the vulnerability and exposure of human and natural systems. Changes in both the climate system and socioeconomic processes are central drivers of the core components that constitute risk. Definitions of terms are provided in the box below.

The use of climate information for impact and vulnerability assessments in decision-framing has followed both top-down and bottom-up approaches. In a top-down decision process, global-scale climate models are used to generate downscaled projections at spatial scales of interest; then they are bias corrected and applied (e.g., as input to a hydrological or a pavement performance model) to estimate the impact on a desired endpoint due to climate change.

However, Garcia et al. (2014) noted that this process often allots significantly more effort and resources to assessing the climate impacts while ignoring other uncertainties that could be more important for near- and medium-term decision making. In a bottom-up approach, on the other hand, the vulnerability of the system is identified first, and then the expected climate impacts are mapped onto this domain to evaluate potential risks to the assessed system. This facilitates the assessment of a broader range of decision-relevant uncertainties, including climate, from a user perspective and has been shown to be useful, for example, in assessing the impacts of climate change on hydrological resources and its vulnerability (Garcia et al. 2014). The challenge with the bottom-up approach is that if a new vulnerability is identified, then the whole process has to be repeated.

Definition of Terms in Figure 1

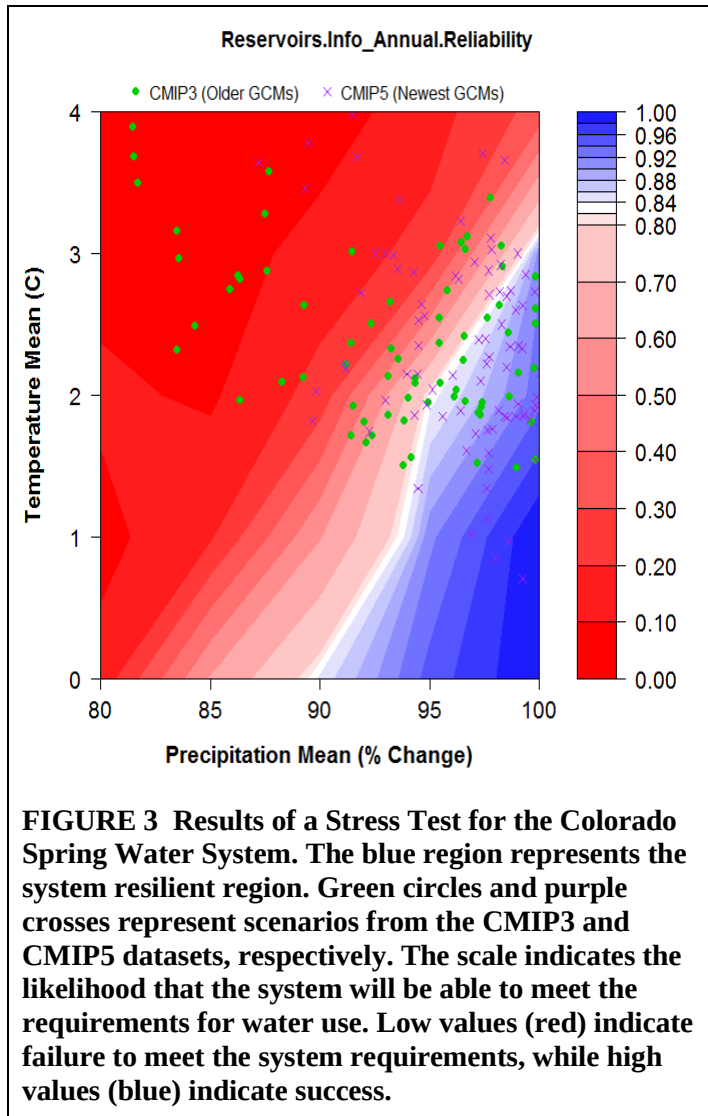
Exposure: The presence of people or important infrastructures in potential harm's way.

Hazard: The potential occurrence of a natural or human-induced physical event that may cause injury, damage, etc.

Risk: Represented by the following expression: $(\text{Probability of Event}) \times \text{Consequences}$. Risk results from the interaction of vulnerability, exposure, and hazard.

Vulnerability: The propensity to be adversely affected, or susceptibility to harm. Numerous factors determine vulnerability, including wealth, social status, gender, and age.

Figure 3 illustrates an approach that begins with a decision-making framework and focuses on establishing system vulnerability before applying specific climate scenarios. The example concerns the vulnerability of a water resource system; it is taken from the University of Massachusetts SERDP project (RC-2202; Brown et al. 2012). The approach links bottom-up vulnerability assessments with multiple sources of climate information. In this approach, a climate “stress test” is applied to a system to determine, for example, what combinations of change in temperature and precipitation lead to unacceptable system performance. This describes the system vulnerability. Then various sources of climate change information may be overlaid on the results of the stress test to determine the likelihood of system failure given the suite of climate change scenarios. This approach eliminates the need to use only specific sets of climate scenarios; instead, a wide range of climate scenarios from a variety of sources was used (Figure 2), showing that under a subset of the CMIP3 scenarios, projected change would result in system failure.



2 THE BASIS FOR FUTURE PROJECTIONS

Despite the proliferation of climate projections at spatial scales ranging from individual weather stations to tens of miles, produced by both regional climate models and empirical statistical downscaling models, identifying the most appropriate inputs to a specific application remains a challenge. The time horizon, the physical geography, the nature and cost of risk versus resilience, and even the degree of uncertainty in climate projections and in other aspects of the future all act together to determine the type of information that is needed and the limits of what can be accomplished with that information.

In this section, we review the extent to which climate projections are required—or not—for various applications; discuss the emission and concentration scenarios that encompass a range of possible futures from human choices regarding energy and land use; and end by explaining how GCMs are used to simulate the impacts of these scenarios on the various regions of the world, thus forming the basis for the future projections that can then be downscaled to impact-relevant spatial and temporal scales.

2.1 WHAT TYPE OF CLIMATE INFORMATION IS REALLY NEEDED?

The need for credible information about future climate to aid in decision making is becoming more urgent, as recently recognized by the U.S. government (GAO 2015). However, there are many different sources of information and methods to choose from. Over the last few decades, a number of different methods for developing future climate scenarios have been developed. Carter et al. (2007) present an excellent overview of different means of representing future climate conditions. These range from simple sensitivity analyses—wherein the climate variables are systematically changed by incremental amounts and the responses of impacts models are then tested—to analogs based on past recorded conditions that may be considered representative of the future, such as using the Dust Bowl conditions in the 1930s in the central Great Plains to predict how current agricultural production would fare were such an event to occur again (Easterling et al. 1993). For near-term climate changes in the next 10 years or so, a useful approach for observed trends in, for example, temperature and precipitation that are significant and consistent with longer-term projected changes (Hurrell et al. 2010) is to extrapolate current historical trends to estimate future changes. In general, however, the use of output from climate modeling experiments to quantify impacts over multi-decadal timescales, often downscaled to a higher resolution, has dominated the field of climate impacts assessment.

It is important to point out that, for some analyses, quantitative information about the future may not be necessary. For example, knowing that summer temperatures will increase in a region, without knowing by exactly how much, could provide sufficient incentive to adapt to heat stress. 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.

For other applications, however, detailed high-resolution climate projections may be useful to determine potential impacts and to scale appropriate preparedness actions. Such applications include those where science is able to provide trusted quantitative projections and when such information is needed for planning. 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. In Section 3 we summarize available inputs and tools for these and other such situations to provide the reader with the necessary information to make decisions based on a solid understanding of the science and available scientific tools.

Quantitative climate projections often can be used as input to other models that translate impacts into additional quantitative information that is directly relevant to future planning. Examples include:

- **Hydrological models**, which can translate climate projections into streamflow, drought or flood risk, or groundwater levels;
- **Infrastructure integrity assessments**, which through damage models/fragility curves translate climate information into risk of exceeding design thresholds or the need to alter maintenance plans;
- **Agriculture or crop models**, in which climate projections can inform everything from crop choice to water management strategies;
- **Energy demand models**, which estimate future need for heating in winter and cooling in summer, the energy for which tends to be provided by distinctly different sources; and
- **National security frameworks** to assess the impacts of a changing climate on food, water, and energy security here in the United States and around the world.

In all of these cases, it is usually possible to identify quantitative projections to use as input to calculate projected changes and the associated uncertainty surrounding those changes over the coming century. More often than not, those quantitative projections are derived from GCMs driven by future emission or concentration scenarios.

2.2 FUTURE EMISSION AND CONCENTRATION SCENARIOS

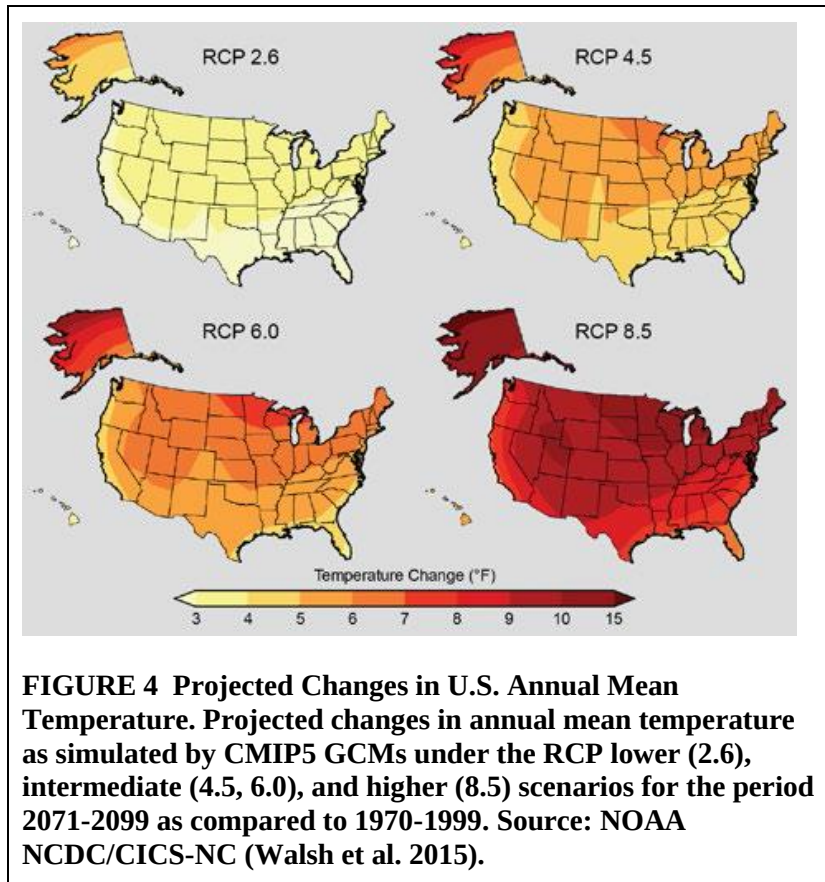
Human choices contribute to a range of plausible climate futures. The IPCC scenarios are intended to cover that range. These scenarios are neither predictions nor forecasts. Instead, the scenarios offer a systematic approach to model socioeconomic pathways for the rest of the century and beyond. Which scenario—if any—eventually becomes reality will depend on the choices being made by human society now, and over the next few decades.

Two major approaches to developing scenarios of future emissions or concentrations of greenhouse gases have been used, the first embodied in the Special Report on Emissions Scenarios (SRES; Nakicenovic and Swart 2000) and the second in the more recent scenarios referred to as RCPS (Moss et al. 2010). The SRES scenarios use socioeconomic modeling to inform potential emissions trajectories, while the RCP scenarios are named after the radiative forcing that would result from each scenario (e.g., RCP 8.5 corresponds to an increase of 8.5 watts per square meter at the tropopause, the boundary between the troposphere or lower atmosphere and the stratosphere) and are based on an internally consistent set of socioeconomic assumptions (including demographics and energy use). Despite differences in development and nomenclature, both SRESs and RCP scenarios encompass coherent, internally consistent, and plausible descriptions of a possible future state of the world (Carter et al. 2007); for the user, it makes little difference how the original scenarios are framed if the end goal is climate projection. Within both the SRESs and the RCP family of scenarios, however, the specific scenarios used can have a substantial impact on the resulting analysis.

Uncertainties in socioeconomic development, energy use, and resulting human emissions of greenhouse gases result in substantial uncertainties in the magnitude of future climate change. These uncertainties increase as they are projected further out into the future (e.g., more than 30 years). At the higher end of the scenarios, atmospheric carbon dioxide levels under the RCP 8.5 scenario reach more than 900 parts per million by 2100. At the lower end, under RCP 2.6, policy actions to reduce carbon dioxide emissions below zero before the end of the century (i.e., to the point where humans are responsible for a net uptake of carbon dioxide from the atmosphere) keeps atmospheric carbon dioxide levels below 450 parts per million by 2100. Projected increases in global mean temperature under the RCP scenarios by the end of the century range from 2 to 8°F (1 to 5°C), depending on the RCP scenario used. For the United States, as illustrated in Figure 4, projected increases range from 3.5°F (2°C) under the lower RCP 2.6 scenario to nearly 10°F (5.5°C) under the higher RCP 8.5 scenario.

2.3 GLOBAL CLIMATE MODELS

Scientists have amassed a vast body of knowledge regarding the physical world. Unlike many areas of science, however, scientists who study the Earth's climate cannot build a "control Earth" and conduct experiments on this Earth in a lab. To experiment with the Earth, scientists instead use accumulated knowledge to build climate models, or "virtual Earths." In studying climate change, these virtual Earths allow scientists to integrate and evaluate different kinds of knowledge of how the climate system works. The models can be used to test scientific understanding of how the Earth's climate responded to past changes (e.g., the transition from the



last Glacial Maximum to our current warm interglacial period) and to develop projections of future changes (e.g., the response of the Earth's climate to human activities).

The most complex of type of climate models are three-dimensional GCMs. These physically based models include the explicit solution of energy, momentum, and mass conservation equations at millions of points encompassing the atmosphere, land, ocean, and cryosphere in every time step. The original atmosphere-ocean modeling components of GCMs were known as general circulation models, after their ability to simulate

the circulation of the atmosphere and ocean. More recently, capabilities for the explicit simulation of the biosphere and atmospheric chemistry have been added to GCMs; these models are typically referred to as global climate models or, if they also include dynamic carbon cycles, as Earth system models (ESMs). Today's GCMs and ESMs encapsulate the great expanse of current understanding of the physical processes involved in the climate system, the interactions of these processes, and the performance of the climate system as a whole. They have been extensively tested relative to observations and can reproduce the key features found in the climate of the past century.

CMIP5 GCMs have a spatial resolution ranging from about 30 to 200 miles (or 50 to 300 km; here, resolution refers to the width and length of the average grid cell). Most of the simulations were performed with models that have a resolution of 60 miles (or 100 km) or more, but a few selected simulations use higher-resolution models. In general, these models can generate mean temperature changes at regional scales with a fair degree of confidence and mean precipitation with less confidence (IPCC 2013). However, because of their relatively coarse spatial resolution the models fail to capture features of climate that are driven by processes or physical features of the earth system that operate at smaller spatial scales. These include the influence of terrain and coastal environments; sub-grid-scale phenomena such as spatial variability of precipitation, tornadoes, and thunderstorms; and other similar severe weather phenomena. At larger spatial scales, the models successfully simulate, but cannot fully replicate, the observed temporal variability and global impact of semi-periodic climate cycles such as the El Niño Southern Oscillation (ENSO) events. As described further in the box below, the next

generation of global models incorporates higher resolutions (25 to 50 km) that better resolve topography and its effects on synoptic weather, and are improving model ability to simulate hurricanes and other storms.

Future of GCMs

Today's GCMs require enormous computing resources to capture the geographical details of climate. Currently, the typical spatial resolution of GCMs run over 150 years is about 1.5 degrees latitude and longitude. For CMIP6, the next generation of such simulations, typical resolutions will increase to 1 degree for century-long simulations. Already, experimental atmosphere-only simulations have been run at a resolution of 15 miles (25 km).

Over the next decade, computer speeds are predicted to increase another thousand-fold or more, permitting GCMs to explore even more details of the climate system. As these analyses become available, they could greatly enhance understanding of severe weather trends in the changing climate thanks to improved treatment of orographic effects on weather patterns. A 2012 National Academy study, *Advancing Climate Modeling* (Bretherton et al. 2012), estimated that global models could be run in long-term mode (i.e., producing multiple decades' worth of output) at about 5-mile (or 10-km) resolution within the next 7 to 8 years. These runs will enable new findings from high-resolution downscaling studies through either dynamical or statistical downscaling.

2.4 UNCERTAINTY

Projected changes in future climate are subject to important uncertainties in the magnitude, timing, and distribution of that change. These uncertainties can be grouped into three primary categories, as follows (Hawkins and Sutton 2009, 2011; Ekstrom et al. 2015): natural variability, human uncertainty (as expressed by emission or concentration scenarios), and scientific uncertainty (as captured by global model simulations).

Natural variability is the result of interactions between components of the climate system such as the atmosphere, the ocean, and the biosphere. Some aspects of variability are somewhat periodic, such as ENSO; others are random or chaotic. These natural variations in the climate system cause temperature, precipitation, and other aspects of climate to vary from year to year and even decade to decade, causing them to be an important source of uncertainty over shorter timescales ranging from 0 to 30 years. Recent studies indicate that natural variability could contribute to uncertainty at even longer timescales up to 50 years on local to regional spatial scales up to 60 miles (or 100 km; Deser et al. 2014). To address uncertainty due to natural variability, future projections should focus on changes occurring over climatological timescales of two to three decades, rather than the changes projected to occur by a given year or even decade.

Future emissions or human uncertainty, as expressed by the future emission or concentration scenarios described in Section 2.2, captures the way future climate change will respond to emissions from human activities that have not yet occurred. Ranges of emissions, concentrations, and resulting temperatures are simply different ways of measuring and expressing uncertainty in possible future changes as a function of human choices. Although all scenarios are intended to be plausible, the actual pathway or magnitude of emissions could be

altered by policy changes triggered by, for example, severe weather events in which climate change may be perceived as a contributing factor, or new technologies for capturing carbon from the atmosphere that become commercially viable. Nonetheless, the substantial range between higher and lower scenarios is sufficient to illustrate the potential range of changes that may be expected, and how these changes depend on future emissions.

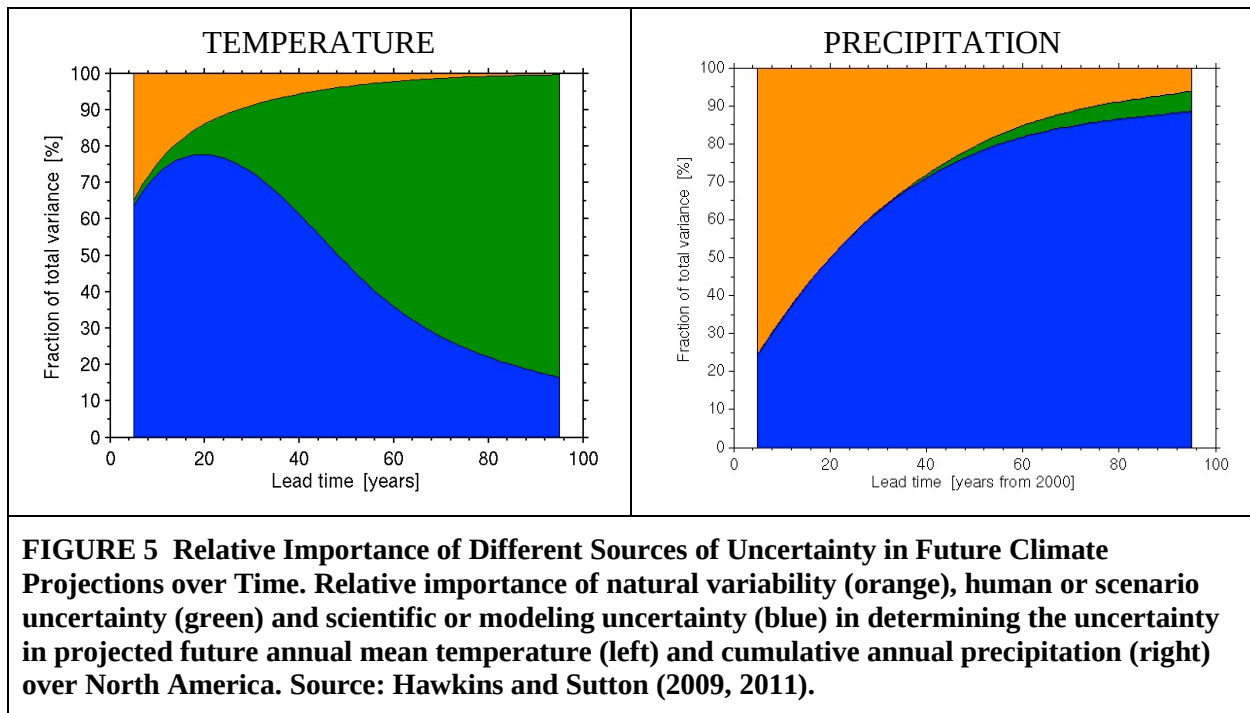
Over shorter time horizons, there is little difference between the magnitude of change projected under a higher or a lower scenario. Near-term climate change is insensitive to scenarios for two reasons: (1) the inertia in the climate system response to emissions and (2) the inertia of energy infrastructure response to policy changes. Scenario uncertainty becomes most important over the second half of the century as the various scenarios within the SRES and RCP families diverge. It is evident in temperature-related projections—both means and extremes—and in some regions its impact can also be seen in patterns of seasonal and heavy precipitation (Solomon et al. 2011). While scenarios cover a broad range of future change, no single scenario can be judged to be more likely than the others at this time. To address human uncertainty, decisions should assess the consequences of multiple scenarios to appropriately bound risk if the planning horizon is longer than 30 years. Further recommendations are provided in Section 4.

Climate Model Uncertainty, as expressed by the range of projections from multiple GCMs, addresses how the Earth’s climate system will respond to increased concentrations of greenhouse gases in the atmosphere. Differences between the GCMs reflect the limitations of scientific ability to simulate the climate system. Model uncertainty can be *parametric* (how does the model represent physical processes, such as cloud formation and precipitation, that occur at spatial and/or temporal scales far smaller than the model can resolve?) and *structural* (are all the processes in the model correctly represented, and are any relevant processes missing?).

Although it is certainly suggestive of model ability, or lack thereof, the magnitude of model biases in climatological values does not necessarily correlate with model ability to reproduce observed and simulate future change. Studies have found, for example, that the order in which GCMs would be ranked from best to worst based on their average biases in climatological temperature is not the same as when these GCMs are ranked based on their ability to simulate observed temperature trends (Jun et al. 2008; Giorgi and Coppola 2010). For most purposes, the use of a multi-model ensemble of GCM simulations with an equally weighted mean generally provides a more robust picture of future conditions than any one model or small subset of models (Weigel et al. 2010; Raisanen et al. 2010; Tebaldi and Knutti 2007). Further recommendations are provided in Section 4.

Future projections can be selected to specifically address each of these three sources of uncertainty and combinations thereof. Figure 5 illustrates how the relative importance of these three sources changes, depending on what timeframe is considered. Over nearly all timescales, model uncertainty remains important.

Over timescales shorter than a few decades, changes in global and regional temperature and other climate indicators are relatively unaffected by differences in future emissions or concentration scenarios. Therefore, when assessing potential climate change impacts within the next 30 years or so, choice of emission or concentration scenario is virtually irrelevant. The



natural variability of climate, however, plays a dominant role in near-term uncertainty and can be addressed by either using ensembles generated from multiple models or using a single model ensemble that captures climate variability at these timescales and spatial scales.

Over longer timescales, beyond about 30 years, scenario uncertainty becomes increasingly important. For most questions, at least two future bounding scenarios should be used to cover a range of possible outcomes and answer important questions. For example, what is the full range of plausible change, including scenario uncertainty? What is the likely minimum amount of change to which a system will have to adapt under a lower scenario (i.e., identifying minimum adaptation thresholds)? What is the maximum amount of change that can be expected under a higher scenario, and what are the boundaries of the change (maximum and minimum)? The choice of bounding scenarios should reflect the type of decision being made, the time horizon over which the decision has to be operative, and the decision-makers' tolerance for risk. In some cases, it may be possible to only use one scenario, in which case a higher-end scenario is recommended for two reasons: (1) despite the recent Paris Accord, the higher-end scenario is the trajectory we have been following most closely for the last decade or more, and (2) if one can adapt to the higher-end scenario, then one can likely adapt to lower-end ones. However, a more robust approach would include multiple scenarios generated using multiple models to cover a range of model uncertainties and emission or concentration uncertainties.

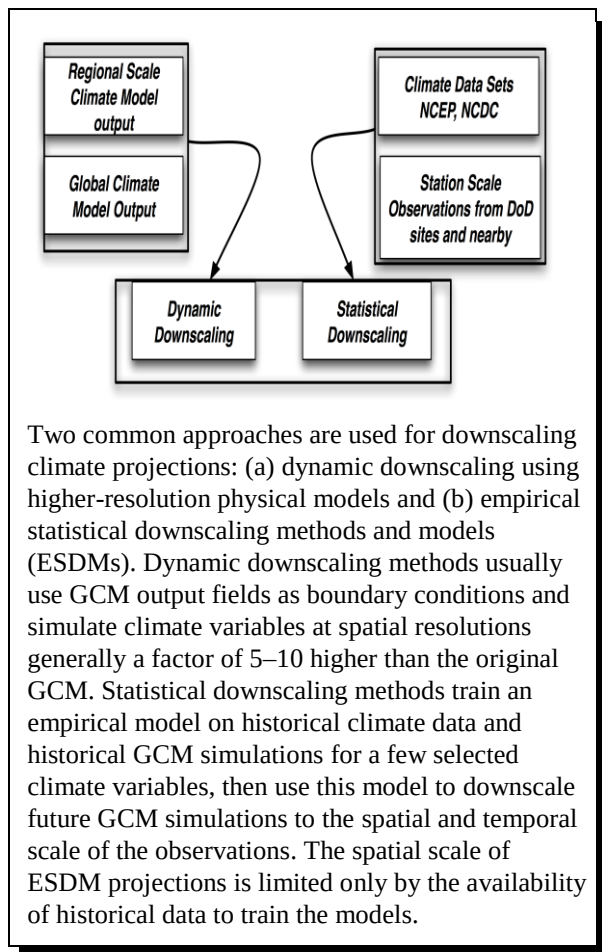
In addition to natural variability and human and climate model uncertainty, local or downscaling uncertainty results from the many factors that interact to determine how the climate of one specific location will respond to global-scale change over the coming century. To address local uncertainty, GCM simulations are typically downscaled to a finer resolution, as discussed in Section 3.

3 INTRODUCTION TO DOWNSCALING

Regional climate change impact assessments evaluate the potential effects of climate change on issues of interest to that region. Such issues could consist of projected changes in crop yield or livestock production; geographic or phenological shifts in a specific invasive or at-risk plant, animal, or bird species; impacts on the functionality of the regional ecosystem as a whole; changes in water or energy supply; or impacts on climate-sensitive economic sectors. These assessments' results provide key input to the development of robust strategies to increase the resilience of both human and natural systems to coming change. They also provide important guidance regarding the allocation of limited resources to encourage adaptation and support resilience in vulnerable areas.

Some regional impact assessments can be performed using GCM output; however, many more assessments (see, for example, Hayhoe et al. 2004; Wuebbles et al. 2010) are informed by regionally specific climate information. The resolution of such information must be much finer than that of the typical GCM, because climate change impacts relevant to stakeholders tend to occur at small scales—often, to specific facilities or locations. This limitation is particularly acute in two situations: first, when estimating changes at the tails of the distribution of daily values; and second, when topography and geographical features not fully resolved by the climate model are key drivers for locally relevant atmospheric phenomena.

To overcome this discrepancy in scale, a broad suite of dynamical and statistical methods—collectively known as downscaling techniques—have been developed to translate climate model output into the spatial (and sometimes even temporal) scales required to answer the urgent needs of decision-makers. This includes developing inputs that can be directly used as input to impact, environmental process, and adaptive response models. Downscaling methods convert GCM output into projections that are more representative of regional-scale changes, both in terms of spatial resolution and by capturing key phenomena that occur at these smaller spatial scales.



In this section, we describe the nature and components of dynamical and empirical-statistical downscaling models; we list examples of datasets where downscaled information is

readily accessible; and we end with a comparison of the relative strengths and limitations of each type of downscaling.

3.1 DYNAMICAL DOWNSCALING

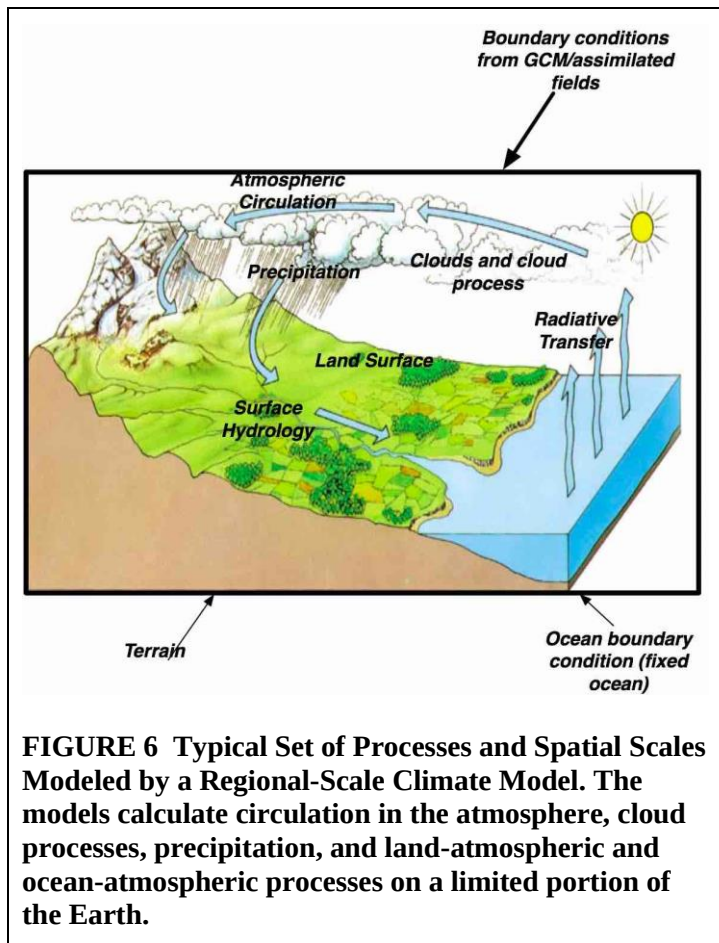
Limited-area climate models play an important role beyond that of the global model. They resolve processes that occur below the spatial scale, or grid size, of a global model; they are able to model complex terrain including complex coastlines as well as processes that are affected by changes in land use and land cover; and they can simulate hydrology at scales of interest to decision-making. The models can be used for dynamical downscaling in two ways: first, through use of a limited-area model driven by GCM inputs after the GCM simulation has finished; and second, through a variable-resolution model at the global scale that “zooms in” on the area of interest during its calculations. The first approach is typically referred to as regional climate modeling, whereas the second approach is often known as variable-resolution modeling. Both are said to be “dynamic” because they directly simulate the dynamics of the regional climate system.

High-resolution models were initially based on weather prediction models. Now, many new sub-models have been added so that the models perform better over timeframes of years to decades. Regional models are similar to GCMs in many ways. Both global and regional models are physical models that can directly simulate many different processes affecting the atmosphere, ocean, and land surface at the spatial scale of the grid cells being used (as illustrated in Figure 6). Both types of models use a series of equations and parameters to describe smaller-scale processes, such as cloud formation or atmospheric turbulence, that the model cannot resolve. In addition, both output a series of three-dimensional fields that include temperature, humidity, and a host of other variables such as winds, clouds, and pressure levels throughout the atmosphere. Like global models, regional climate models (RCMs) continue to evolve, both by increasing resolution (as fine as 0.6 to 1.2 miles or 1 to 2 km in some

RCM Evaluation

Assessing a regional model’s performance is difficult and time-consuming, but often necessary to appropriately caveat its results. Although a robust set of regional climate model (RCM) projections will have to include multiple boundary conditions from different GCMs, multiple future scenarios, and potentially multiple regional models, the uncertainty from different parameterizations can be successfully tested using a single model, as many regional-scale climate models have a number of parameterizations for key physical processes (e.g., Leung et al. 2013; Bruyere et al. 2014). For example, it is valuable to understand which model processes might be driving projected changes to determine whether or not model outputs make sense. This is especially important when RCMs differ significantly from global model simulations and even disagree with each other.

A growing body of literature has demonstrated that regional-scale climate models add value to the projections generated by the original GCM (Castro et al. 2005; Di Luca et al. 2012; Wang et al. 2015), and that these models can reduce model-observational differences or biases in the host climate models, often significantly (Mearns et al. 2012; Bukovsky et al. 2013; Leung et al. 2013; Wang et al. 2015; Torma et al. 2015). Higher-resolution models can also improve the spatial-temporal patterns of change (Di Luca et al. 2012; Wang et al. 2015). A challenge from a user’s perspective is that, just as in the case of global models, no single “best” RCM can meet all needs. As with global models, regional model inter-comparisons illustrate the importance of using multiple regional models to capture a good range of model uncertainty.



studies; more commonly 6 to 7 miles, or 10 to 12 km) and by improving the representation of physical processes in the model. In contrast to global models, however, regional models cover only a limited area. At the boundaries of this high-resolution area, dynamical downscaling models require input from a gridded three-dimensional representation of the global atmosphere. This input commonly comes from GCM output, but it also can originate from global weather model output.

The most widely available dynamically downscaled output was generated under the NARCCAP using CMIP3 output to provide boundary conditions. The NARCCAP dataset includes one forcing scenario (the mid-high SRES A2 scenario), and multiple regional-scale models at a spatial resolution of 50 km for the periods 1971–2000 and 2041–2070 (Mearns et al. 2013). NARCCAP

output has already been extensively used in impacts research (see Mearns et al. [2015] for a review). The ongoing North American Coordinated Regional Downscaling Experiment (NA-CORDEX) is performing similar simulations using multiple CMIP5 GCMs and multiple RCMs at a spatial resolution of 25 km based on one or two forcing scenarios (RCP higher 8.5 and lower 4.5) for the time period 1950 to 2100 (see WCRP undated).

3.2 EMPIRICAL STATISTICAL DOWNSCALING

The field of empirical statistical downscaling encompasses a broad range of techniques, from simple approaches that can be calculated in a spreadsheet to complex stochastic models with computational demands approaching those of a RCM. They range from methods that simply correct for bias (the difference between the historical model simulation and observations) to methods that develop relationships between local weather and the larger-scale atmospheric conditions simulated by global models. Statistical techniques run from simple linear regression (e.g., Wilby and Wigley 2000) to more complex applications based on weather generators (Wilks and Wilby 1999), canonical correlation analysis (e.g., von Storch et al. 1993), artificial neural networks (e.g., Crane and Hewitson 1998), inhomogeneous Markov models (e.g., Vrac et al. 2007; Fu et al. 2013), and non-parametric kernel density estimators.

An ESDM typically uses statistical relationships to translate GCM output into high-resolution future projections. High-resolution climate model simulations can be developed based on different types of observational data, as long as there is a record of sufficient length (typically 20 years or more) to cover as large a range in weather conditions as possible. A record that is too short can create sampling problems, wherein the statistical model is trained on a set of conditions that do not encompass the full range of weather at that location. Inputs can include weather station data, which corresponds to an individual location or gridded data; this can be derived from weather station data that has been smoothed and interpolated onto a regular grid, from reanalysis or other types of assimilation that merges multiple data sources and models to produce a single dataset, or even from satellite datasets. In ESDMs, local conditions are assumed to be a function of three factors: larger-scale atmospheric conditions and weather systems that vary from day to day; local topographical, coastal, and geographical factors that do not vary much over time; and day-to-day variability (noise) that averages out over time.

There are two approaches to training a statistical downscaling model. The first approach establishes a relationship between large-scale atmospheric features (which can include temperature, precipitation, humidity, pressure, winds, and more) and the observed variables of interest.

The second approach takes the variables of interest from a host GCM (i.e., temperature, precipitation) and disaggregates these values onto the spatial scale of the observations. The difference between observations and GCM simulations at the scale of the observations is then

ESDM Evaluation

ESDM performance can be evaluated in at least three distinct ways. Each of these methods yields different information regarding the ability of the ESDM to simulate historical and/or future change.

First, when downscaled climate projections are compared the historical observations used to train the model *for the same time period used in training*, the difference between modeled and observed variables yields insight into the *goodness of fit* of the statistical model. Second, when the same comparison is conducted *for an independent time period not used in training*, the difference between modeled and observed variables yields insight into the *generalizability* of the statistical model. Neither difference is expected to be zero; in the first case that would signify over-fitting of the statistical model, and in the second, a perfect sampling of natural variability far beyond the length of typically available observational datasets.

A third way to evaluate ESDMs is through the “perfect model” experiment, where ESDM-based future projections based on coarsened GCM output fields can be compared to future projections from the original high-resolution version of the same GCM (Dixon et al. 2016). This approach yields insight into the stationarity of the statistical model, at least in comparison to the GCM, which can vary by region, by variable, and by quantile (e.g., averages versus extremes).

Downscaled historical simulations should not be compared to a different observational dataset than that used in training, as the same information can be derived much more transparently by simply comparing the two observational datasets. Climate projections generated for one dataset are not intended to match observations from a different dataset or a different location. Downscaled simulations should not be compared to a time series that includes both data points used to train the model and data points that were not, because that would make it impossible to differentiate between goodness-of-fit versus generalizability. Last, downscaled simulations should not be evaluated over non-climate time periods: a day, a year, or even a decade. Over short time frames, observations and model simulations do not match—and should not be expected to match—because climate models generate their own patterns of natural variability. Essentially, climate models represent an “alternate Earth,” with the same emissions of heat-trapping gases from human activities and the same overall patterns of natural variability, but different day-to-day and year-to-year conditions.

represented with a statistical model. Regardless of which approach is used, the result is a statistical model that can transform GCM outputs into projections at the scale of the original observations. These can range from hourly observations at a single weather station or set of stations to monthly values for a gridded dataset covering an entire region or country.

Empirical statistical downscaling models are often flexible, enabling them to be tuned to obtain finer-resolution output for targeted variables and for selected locations. Because they are easy to use, they tend to lend themselves to a wide variety of applications to assess the impacts of climate change (e.g., Kattenberg et al. 1996; Hewitson and Crane 1996; Giorgi et al. 2001; Mearns et al. 2001; Wilby et al. 2004; and references therein). Such methods have been used to provide the basis for regional climate assessments for various states, regions, and government agencies (e.g., Hayhoe et al. 2004, 2008, 2010; USGCRP 2009; Steinschneider et al. 2015; for a review of the use of these methods over North America, see Mearns et al. 2014). The most widely available statistically downscaled datasets and models are summarized in Table 1.

3.3 COMPARISON OF DYNAMICAL AND STATISTICAL DOWNSCALING METHODS

There have been a number of reviews and assessments of downscaling techniques over the last several decades (e.g., Giorgi and Mearns 1991; Wilby and Wigley 1997; Giorgi et al. 2001; Christensen et al. 2007; Mearns et al. 2014; Ekstrom et al. 2015); some of these reviews also provide recommendations for proper use. As Ekstrom et al. (2015) point out, a key aspect of any downscaling method is its ability to simulate realistic climate and physically plausible change. Table 2 combines information from many of these sources along with our own expert judgment to summarize the primary strengths and limitations of each.

In general, the information derived from GCMs, RCMs, and ESDMs is useful for impact assessments. GCMs and RCMs rely primarily on physical process-based descriptions of atmospheric phenomena. These may be limited by deficiencies in current scientific understanding of some of the atmospheric phenomena, but they have been shown to reproduce most of the key features of the observed atmosphere (IPCC 2013). ESDMs rely on a combination of observations and statistical models. Although limited by the assumption that historical relationships between observations and GCM simulations maintain their validity in the future, more complex ESDMs are able to reproduce many of the higher-resolution features of a physically based model (Dixon et al. 2016). In this section, we expand on the primary strengths and challenges of each method.

Compared to global models, the RCMs used in *dynamical downscaling* operate at a much higher spatial resolution and provide meaningful output that can be archived at less than daily frequency and at grid resolutions that can be up to a factor of 10 higher. This offers a number of opportunities not available in GCM output, including the ability to explore projected changes in extremes in precipitation, temperatures, and other relevant indicators (Tripathi and Dominguez 2013). Methods for generating these extremes from model projections are rapidly evolving (Wang et al. 2016); however, further research is necessary to make this into a useful product for decision support. In addition, higher resolution also implies an extremely high

TABLE 1 Summary of Widely Used Statistical Downscaling Methods, an Example of Each Method, and Characteristics of Available Outputs^a

Statistical Method	Sample Dataset or Model Using This Method ^b	Geographic Extent and Spatial Resolution	Temporal Resolution	Variables
<i>Delta:</i> ^c Differences between GCM historical and future projections are added to historical observations	WorldCLIM dataset	Global (from 1/120 to 1/60 degrees)	Monthly by decade from 2020s to 2080s	Maximum, minimum temperature; precipitation; and bioclimatically active variables (see WorldClim [undated] for list)
<i>Bias Correction:</i> ^d The difference or bias between the historical GCM and observations is used to correct historical and future GCM projections	MBC (monthly bias correction) model corrects mean + standard deviation	N/A	N/A	Maximum, minimum temperature; precipitation
<i>Empirical Quantile Mapping:</i> ^{d,e} Historical data are used to correct monthly GCM output and observations; monthly model bias corrected using an empirically determined value for each quantile (e.g., by subtracting one cumulative distribution from the other, as in the CDFT, EDQM models)	BCSD (bias correction—spatial disaggregation) dataset CONUS and southern Canada (1/8 degrees)	Monthly and daily (by sampling from daily observations) outputs	1950–2099	Maximum, minimum temperature; precipitation; monthly hydrology; and wind
<i>Parametric Quantile Mapping:</i> ^f Historical data are used to correct daily GCM output; daily model bias is removed by a parametric (fitted) correction for each quantile	ARRMv1 (asynchronous regional regression model) dataset	CONUS (1/8 degrees), Alaska (1/2 degrees), North and Central America (individual weather stations)	Daily 1960–2099	Maximum, minimum temperature; precipitation; humidity (at stations only); derived temperature and precipitation thresholds and other secondary indicators

TABLE 1 (Cont.)

Statistical Method	Sample Dataset or Model Using This Method ^b	Geographic Extent and Spatial Resolution	Temporal Resolution	Variables
<i>Constructed Analogs:</i> Historical observations are used as an analog for model-simulated climate; a spatial matching scheme is used to select an appropriate analog days from observations and replace the GCM-simulated day with its climate	LOCA (localized constructed analogs) dataset	CONUS (1/16 degrees)	Daily 1950-2100	Maximum, minimum temperature; precipitation
<i>Weather Generator:</i> ⁸ Monthly GCM data is bias-corrected using linear regression, then a stochastic weather generator is used to produce daily output	SDSM (statistical downscaling model) available as personal computer software	Global (individual weather stations)	Daily	Maximum, minimum temperature; precipitation
<i>Canonical Correlation Analysis:</i> ⁸ Corrects GCM output using a statistical model that quantifies the relationships between two multivariate sets of variables including both upper-air and surface	ESD4ALL model (empirical statistical downscaling for all) available as R code	Global (individual weather stations)	Daily	Maximum, minimum temperature; precipitation

^a This table summarizes several of the commonly used statistical methods that have been used to develop high-resolution climate projections for the United States, in approximate order of complexity from simple to more complex. For each method, the table also provides an example of a dataset or a readily accessible software package or model description that uses that statistical method or approach. This list is not comprehensive; it is simply intended to illustrate the range of available information.

^b Sources: WorldCLIM—WorldCLIM (undated); MBC and NBC—Sachindra et al. (2014); BCSD—Reclamation et al. (2014); ARRM—USGS (undated); LOCA—Pierce (undated); SDSM—(www.sdsm.org.uk); ESD4ALL—inside-R (2016).

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TABLE 1 (Cont.)

^c The delta method is the oldest method used to generate higher-resolution information from GCM output. It has been in use since the mid-1980s, and it is still in use today. For temperature (mean, maximum, and minimum) the difference between the relevant future time period and the current period is calculated and then that change is added to observed temperature data. Most often, monthly mean changes are calculated and then added to observed data at monthly down to daily timescales. Thus, only the mean change in temperature is used and only the mean of the future distribution is changed, not its shape (which may affect the realism of the probability of extremes at either tail of the distribution). For precipitation, the change is usually calculated as a percentage change in precipitation. The observed precipitation (monthly or daily) is multiplied by the ratio of the future precipitation to the current precipitation from the model. If this ratio is used to modify daily observed data, several limitations occur. First, the frequency of precipitation is not changed, but the variance is (increased if the ratio is greater than 1 and decreased if it is less than 1). An example of application of this method is the SNAP (Scenarios Networks for Alaska-Arctic and Planning) dataset (<https://www.snap.uaf.edu/methods/downscaling>). See Mearns et al. (2001) for a more detailed view of the delta approach.

^d A number of statistical downscaling models incorporate bias correction into their framework. Such methods first use historical observations to correct the bias in the GCM (or RCM) by empirically mapping the monthly distribution of GCM values onto the observed distribution. Spatial disaggregation is then used to achieve finer spatial scales. Some examples of the models that belong to this class are bias correction–spatial disaggregation (BCSD), monthly bias correction (MBC), nested bias correction (NBC), and kernel density distribution mapping. The BCSD model developed by Wood et al. (2002) used monthly averaged GCM calculated temperature and precipitation output. The model output is bias corrected using gridded observations (e.g., Maurer et al. 2008) that are scaled to the grid size of the model. The bias corrected model output is then scaled to the spatial scale of interest, typically the point of observations that are sub-grid scale to the model. A final step performs time disaggregation using daily patterns from observational datasets to scale the monthly projections. The MBC (Johnson and Sharma 2012) is similar in concept to the BCSD, in that the monthly averaged mean and standard deviation of the precipitation from the GCM downscaled to an observational location is corrected with observed precipitation. The bias corrections for the future climate are assumed to be the same as the past climate for this method (i.e., stationarity is assumed). In addition, the NBC (Johnson and Sharma 2012) bias corrects the monthly mean and standard deviations of the downscaled precipitation, as well as correcting the autocorrelation lag between the present and the next month and correcting an annual precipitation autolag for the present year compared to the next. These methods are commonly applied in hydrological assessments (Sachnidra et al. 2014). Some evidence is emerging that the stationarity assumption may hold under some conditions in the future (Teutschbein and Seibert 2013).

^e Cumulative distribution function (CDF) based approaches attempt to downscale the entire statistical distribution of the variable to a local distribution rather than a mean value of a climate variable or its standard deviation. The EDQM method uses the difference between the observed CDF and modeled CDF for the present to calculate a correction that is applied to modify the projected CDF from a GCM (Li et al. 2012). The CDFt method is different in that a weather typing scheme is used to correlate a synoptic-scale CDF with a locally observed CDF to obtain a downscaled or transformed CDF. As explained by Michelangeli et al. (2009), “the CDFt method assumes that there is a translation available for translating a CDF of a GCM variable (e.g., temperature) to a local scale CDF.” KDDM first estimates a PDF of a distribution (e.g., temperature from observations and a model) using a non-parametric method and integrates the PDF into the CDF. The transfer function is then built using these empirical CDFs (McGinnis et al. 2015).

Footnotes continued on next page.

TABLE 1 (Cont.)

^f Parametric quantile mapping is similar to empirical, except that the bias correction is accomplished by ranking observed daily and historical model-simulated daily values by month, then fitting a parametric equation to their quantile-quantile (q-q) relationship. This approach generalizes the relationship between observations and model simulations to an extent that permits the use of daily, rather than monthly, inputs. A widely used example of this method is the asynchronous regional regression model (ARRM v1; Stoner et al. 2012), which uses piecewise linear regressions to build monthly q-q relationships based on daily data; as such, it is expected to better represent the tails of the distribution than approaches based on monthly simulations alone. ARRM can be applied to both gridded and individual weather station observations, which enables the downscaling of additional variables including maximum, minimum, and daily average humidity and solar radiation.

^g Canonical correlation analysis and the statistical downscaling model (SDSM; Wilby et al. 2002) differ from the models described above in that the predictands and predictors are not the same variables. The SDSM uses linear multiple regression to relate large-scale upper air variables (e.g., 500 mb heights, humidity, vorticity) to the local impact variable of interest (e.g., daily temperature or precipitation, or both). Regression coefficients are determined using reanalysis data for the large-scale variables and point observations for the predictands. These relationships are then applied to future GCM outputs. These techniques generally reproduce well the current point observations, but as with all of the empirical techniques, it is assumed that the relationships between the predictors and predictands do not change with climate change. In addition, the explanation of variance (for the predictands) is not perfect. Typical R^2 values for temperature are about 0.8 and are even less for precipitation.

When is an RCM useful?

The utility of running a dynamic downscaling model to generate climate projections for decision support systems at regional and local scales can be determined by asking:

- (1) Do the RCMs reduce the model-observational errors (bias) of the projections made by the host GCMs at the regional scale?
- (2) Do the RCMs add significant value to the projections generated by the GCMs, primarily through the addition of previously unresolved physical phenomena?
- (3) Does higher grid resolution lead to a better outcome in projections (i.e., improve the answers to questions 1 and 2)?

In general, the RCMs have been shown to add value compared to the GCM that provided the model boundary and initial conditions (Di Luca et al. 2015, 2016; Wang et al. 2015); they reduce the overall bias and are able to simulate physical processes or phenomena that might otherwise not be resolved. However, this depends on the region being assessed and sometimes on the variable being evaluated. A

computational burden and expense, necessitating carefully designed numerical experiments and analyses (see box to the right).

more detailed description of these regional dependencies is provided in Section 4.

From a scientific perspective, RCMs are subject to many of the same limitations as GCMs. Model structure determines which processes are included in the model and how they are modeled. No matter how high the resolution of the regional model, physical processes that are unknown or that are incorrectly represented may always need to be addressed. Like GCMs, RCMs also require bias correction before using their output in impact assessments.

RCMs also have their own unique sources of scientific uncertainty. One of the most important is their need for boundary conditions. In the case of downscaling, these boundary conditions are generated by a GCM. Boundary conditions are imprecise because they cannot be applied to every grid cell of the regional model at every time step. Most regional models operate at a much higher resolution in both space and time than does a global model. Discovering how to “fill in the gaps” in these boundary inputs—and merge them into the regional model without making it unstable—is a challenging problem. Recent advances in global climate modeling that use continuously variable numerical gridding techniques offer one approach to addressing some of the issues related to downscaling from GCMs and resulting error from the model boundaries in RCMs. Other approaches—such as a hybrid dynamical-statistical technique that combines the advantages of resolving small-scale dynamics of using a dynamical downscaling technique from a GCM with the computational advantages of statistical technique—are under development (Walton et al. 2015).

The **statistical models** used in ESDM generally provide a close match to historical conditions, since statistical models are trained from observations. This bias removal is successful at the temporal scale of the downscaling—that is, seasonal downscaling removes seasonal biases, whereas daily downscaling removes daily biases. In addition, ESDMs are generally cost and time efficient (although the computational demand does increase with the complexity of the method). Depending on the model used, hundreds of years of climate projections can be statistically downscaled using the same computing resources required to run only a few years of an RCM.

Statistical methods, however, also are limited by observations, in at least four ways. First, it is only possible to develop projections for variables that have already been observed for a number of years and for the scale at which they were observed. For some regions of the world, insufficient data are available to use statistical models for downscaling. Second, statistical models cannot be used for important climate variables, such as soil moisture or stream temperature, if they are observed infrequently or in a limited number of locations. Third, in developing the relationships between large-scale and local climate, statistical methods do not typically resolve any of the physical processes responsible for this relationship (although some of these relationships may be implied by the predictors chosen from the global model). Statistical models are trained to reproduce the net effect of all real-world processes, regardless of what they may be. Thus, statistical downscaling models may match high-resolution observations better than RCMs, because statistical models are not limited by scientific understanding of the fine-scale physical processes that affect climate. For the same reason, however, they also can incorporate false signals, like observational error, into the relationship. Last, statistical methods are based on

the fundamental assumption that the relationship between large-scale climate and local climate remains stationary over decades—an assumption that may not always be justified if, for example, climate change alters local feedback processes that affect the relationship between local and large-scale climate.

4 RECOMMENDATIONS/GUIDELINES

Choosing which climate projections or methods to use depends on the question being asked. Some studies only seek to understand the sensitivity of a given system or region to a range of plausible future changes in mean climate. For these, published climate projections (for example, those used in the Third U.S. National Climate Assessments [Melillo et al. 2014] and in the atlas of climate projections produced by the IPCC Working Group I [van Oldenborgh et al. 2013]) or even historical trends can inform adequate estimates of projected changes in regional temperature, precipitation, or sea level. Other studies seek to quantify the projected impacts of climate change for a given timeframe or range of future scenarios. Many of these require quantitative climate projections as inputs, raising questions about model and scenario selection.

Our strongest recommendation for users who require high-resolution climate information is that they work with individuals conversant with the various methods discussed in this document. Although we provide general guidance here, users who are unfamiliar with climate science should seek out individuals with a level of expertise in the use of future climate information from multiple approaches and/or datasets. That being said, this section also provides initial guidance to assist in identifying appropriate climate inputs for impact assessments from either a research or a decision-making context and interpreting the results.

Climate Models: In most cases, it is best to use output from multiple GCMs, although model output obtained from multiple ensemble simulations generated by a single GCM will also cover a substantial uncertainty range, better representing natural variability. Using different models with different physical parameterizations can cover a broader range of model uncertainty. When selecting GCM outputs individually, it is best to favor those with a long development history that are well-documented in the literature. In most cases (a notable exception being the Arctic), attempting to identify a subset of “better” models based on their performance over a region will not necessarily improve future accuracy. The ability of global models to reproduce average temperature or precipitation at the regional scale may have little or nothing to do with their ability to simulate a globally averaged climate. Thus, to select a model for a particular region, it is necessary to evaluate the GCM’s accuracy in projecting regional-scale changes for the region of interest. Although there is no agreed-upon number of acceptable GCMs required make up a representative ensemble, using at least a few GCMs from different modeling centers with long development histories may be sufficient to encompass the greater part of model-related uncertainty.

Future Scenarios: RCP scenarios form the basis for climate model projections of the future. Individual RCP scenarios have no likelihood attached to them. As a result, there is no intrinsic reason to expect a midrange scenario to be more probable than a higher or lower one. For projections beyond several decades, in most cases it is best to use a range of plausible scenarios to reflect the human choices that may lead to different emissions pathways. When using statistical downscaling, it is recommended to use output from at least two future scenarios spanning a range from higher to lower to capture the uncertainty in how human choices affect climate. Dynamic downscaling output is often limited to a higher scenario and should provide the upper boundary for making assessments. If more than one scenario is available from dynamic

downscaling, it is appropriate to use output corresponding to both a higher and lower scenario. Quantifying impacts under a higher scenario provides insight into the impacts that might be avoided by reducing emissions, while quantifying impacts under a lower scenario establishes a minimum requirement for adaptation, even if such reductions were to occur.

Downscaling: It is not possible to provide clear recommendations for different downscaling methods that are appropriate for all assessment and planning efforts. Different methods do produce different high-resolution climate changes (Vavrus and Behnke 2014) and new approaches, such as a “perfect model” framework, are advancing the state of the science in downscaling inter-comparison and evaluation (Dixon et al. 2016). In general, however, a downscaling method should be selected based on its ability to credibly resolve spatial and temporal scales relevant to the question at hand. As previously discussed, two broad types of downscaling models, dynamical (regional climate) and statistical, represent the state of the practice. Both have advantages and limitations that can help in identifying the most appropriate method for a given question. For example, for annual or seasonal means, a simple delta ESDM approach could be adequate. For annual to monthly values, a monthly ESDM approach such as bias correction–spatial disaggregation could be used. For annual to daily values, a daily ESDM approach such as an asynchronous regional regression model (available from the U.S. Geological Survey [USGS] GeoData Portal [Stoner et al. 2012]) or a RCM (available from the NARCCAP: www.narccap.ucar.edu) should be used. Variables that do not have regular historical observations or that are highly dynamical in nature (such as wind direction and speed, solar radiation, and humidity) should use datasets derived from dynamical downscaling based on RCMs.

Uncertainty: For most questions, it is important to consider and quantify uncertainty in future climate projections. Section 2 describes the primary sources of uncertainty in future projections. Using an ensemble of model simulations produced from a range of climate models driven by different future scenarios and timescales is the most commonly adopted method for assessing model uncertainty. Quantification of uncertainty across different climate model simulations can be accomplished through various methods, such as simply representing the range of the climate change across the models, looking at the results via percentiles of the data (e.g., via box plots representing the basic distribution of the results), or producing relatively sophisticated probabilistic models from the multiple climate model results (see Tebaldi and Knutti 2007). More recently, appreciation has increased for the uncertainty contributed by internal variability, which can be represented by different realizations from the same global model; however, at this stage, few climate models provide large ensembles representing internal variability (see Deser et al. 2012).

Climate projections from climate models (and resulting impacts) should always be grouped separately by future scenario to avoid conflating the uncertainty due to human choices—which is not easily quantified, especially in probabilistic terms—with that due to model uncertainty. It is also important to recognize that downscaling techniques themselves can potentially add to the uncertainty; it has been established that different downscaling techniques result in different quantitative details of the climate change (e.g., Wilby et al. 1999; Mearns et al. 1999; Vavrus and Behnke 2014). It is not often, however, that multiple means of downscaling are produced, compared, and combined with the uncertainties from the global

models. Often the multiple uncertainties in the future climate are used as input to impacts models, and then the effect of the uncertainty from the climate on the impacts is analyzed and quantified (e.g., Katz 2002). The impact or process models themselves, as alluded to previously, also contribute to the combined uncertainty of model output, often significantly. Moreover, the temporal and spatial resolution requirements of such models may often exceed what can be provided by downscaled data products.

4.1 RECOMMENDED APPROACH

We cannot recommend a single approach even for the simplest of applications. It is feasible, however, to construct a set of options that could be desirable given the current state of knowledge. The authors who produced this document acknowledge that the development of recommendations should be an ongoing activity, and papers such as this one should be treated as living documents in need of frequent updating. There is a paucity of specific research or guidance documents on how and when to use different types of high-resolution information on climate. The IPCC Task Group on Data and Scenario Support for Impacts and Climate Analysis (TGICA) has provided some recommendations in various guidance documents over time, including one for use of RCM results (Mearns et al. 2003) and for statistical downscaling (Wilby et al. 2004). Ekstrom et al. (2015) provides more recent guidelines and emphasizes the concepts of climate realism (model skill) and physical plausibility of change in considering the use of different methods. They pose a series of questions about the nature of the planned use of the climate information that overlaps with many of our discussions in this document. However, they avoid providing overly detailed recommendations, as do we. Our recommendations are based on, first, identifying a set of criteria that can be used to broadly classify the problems a user would encounter; and next, for each of these criteria, addressing the suitability of using a particular method or an appropriate set of methods. The color-coding in Table 3 should be considered a qualitative ranking and an expert judgment based on our collective knowledge. The following section uses illustrative examples to assist in the interpretation of information in Table 3.

4.2 ILLUSTRATIVE EXAMPLES OF IMPACT AREAS IMPORTANT TO THE U.S. DEPARTMENT OF DEFENSE

A complete description of the many ways in which climate projections can be utilized to quantify future impacts is beyond the scope of this section. Instead, we provide some examples of impacts sectors of concern to DoD, for which climate projections would be feasible and developing assessments and adaptation plans would be desirable.

4.2.1 Human Health

Human health, which is affected by heat stress, is important to the military for performing work and exercise outdoors. Wet bulb globe temperature (WBGT)—which combines the effects of temperature, humidity, solar radiation, and winds—is used to measure different variables that affect heat stress levels (Yaglou and Menard 1957; Budd 2008). A system of specific work-rest

TABLE 3 Evaluation of Available Downscaling Models and Output and Their Limitations

Descriptions	Empirical Statistical Downscaled Datasets										RCM Dataset: SERDP
	GCMs	Delta Correction	Empirical Quantile Mapping	Bias Correction	Parametric Quantile Mapping	Weather Generator	Constructed Analogues	KDDM	NARCCAP	CORDEX	
Model Names	Many	Delta	BCSD, EDQM CDFt	MBC	ARRM V1	SDSM	CR, LOCA	KDDM	Multiple Models	Multiple Models	WRF V3.2
Source	CMIP3/5	Hijmens	Maurer/Wood		Stoner/Hayhoe	Wilby	Hidalgo	McGiniss	Mearns	Gutowski Mearns	Kotamarthi
Computer Storage Format	NetCDF Output	NetCDF Output	NetCDF Output		NetCDF Output	PC Code			NetCDF Output	Netcdf Output	Netcdf Output
Temporal Res [IN]	Daily	Monthly	Monthly	Monthly	Daily	Monthly	Daily	Daily	3 hours/6 hours	3 hours	3hours
Temporal Res [OUT]	Daily	Monthly	Daily	Monthly	Daily	Daily	Daily	Daily	daily	3 hours	3hours
Spatial Resolution	1 degree to 2.5 degrees	Grid: 30 sec. to 10 min.	Grid: 1/8 degree	Same as obs.	Grid: 1/8 degree and individual stations	Individual stations	Grid: 1/8 degree	NARCCAP grid	Grid: 50 km	Grid: 25 km	Grid: 12 km
Output Variables	Many	T(avg) Pr	T(max) T(min) Pr	T(max) T(min) Pr	T(max) T(min) Pr RH (max/min)	T(max) T(min) Pr	T(max) T(min) Pr	T(max) T(min) Pr	53	66	80
Applications											
Can I use the absolute values that come from these sources, or do they have to be bias-corrected?											
Is this method/data adequate for...											
• Annual and seasonal mean temperature and/or precipitation? • Annual temperature and precipitation extremes? • Daily mean precipitation • Decadal temperature and precipitation extremes? • Daily temperature and precip extremes • Hurricanes, winter storms, and other types of large-scale extreme weather events?											

flag days has been established (white, green, yellow, red, and black) with activity restrictions progressively increasing, based on different values of WBGT. On black flag days (WBGT > 90°F) all outdoor activity must cease. Whereas temperature, humidity, and solar radiation can be calculated by some statistical models for airport weather stations with long-term observations of these variables, incorporating changes in wind speed would require output from a RCM.

4.2.2 Hydrology

Hydrology related to military installations involves water resource availability, surface runoff, groundwater, lake levels, and the maintenance of wetlands. Climate impacts on water resources often may be studied using high-resolution projections as input to water resource models. At minimum, these models require information about current and future temperature and precipitation on differing timescales, which can be obtained from a broad range of statistical downscaling models. Additional variables may include solar radiation, wind, and humidity, many of which would require RCM simulations.

4.2.3 Ecology

Climate change impacts on high-impact ecological systems and services relevant to the DoD include coastal inundation, flooding, and wildfires (Grimm et al. 2013). These and other ongoing changes in climate are expected to influence the spatial ranges occupied by species, phenology shifts, and composition of the species in an ecosystem. Temporal changes in the climate, such as the onset of winter and diurnal cycle of temperature and precipitation intensity also are expected to affect species and ecological processes. To assess the impact of these climate changes on ecosystems requires temperature maxima and minima, diurnal temperature profiles, shifts in seasonal cycles, precipitation intensity and frequency changes, and estimates of the risk of wildfires and coastal flooding. Some of these variables are available directly from downscaling models, and others can be derived using model output (e.g., potential for wildfires).

4.2.4 Built Infrastructure

Infrastructure will be affected by a number of different weather and climate phenomena, including flooding due to high precipitation and, in the case of coastal locations, storm surges; extreme storms (e.g., hurricanes); extreme winds (from, e.g., tornadoes and other extreme storms); high temperatures that can warp rails, melt asphalt, and limit airplane take-offs; and heating and cooling degree-days affecting energy demand. The latter can be calculated from maximum and minimum daily temperatures. However, data on changes in severe storms (including hurricanes) are difficult to retrieve from most climate model output and often require specialized higher-resolution RCM simulations that incorporate storm surge models to obtain robust estimates of storm surge heights.

4.2.5 Available Climate Data for DoD Needs and Their Limitations

Table 3 provides a snapshot of the available data products and some of their limitations as of the writing of this report. The availability of climate model output at high-spatial and high-timescale resolution is rapidly improving; this information should be updated as needed. The information in Table 3 primarily refers to the needs of the high-resolution climate model output user discussed earlier; other users may find the limitations discussed here restrictive or irrelevant.

Each column in Table 3 summarizes some of the widely—and primarily freely—available datasets based on GCM output, empirical downscaling methods, and dynamic downscaling. A few are still in development (e.g., NA-CORDEX) and hence are missing some details. Of note is the first column, which describes the most widely available repositories of GCM output generated for the last two IPCC Assessment reports, CMIP3 and CMIP5. Other than the differences in the design of the numerical experiments that generated the dataset for CMIP3 and CMIP5 and the number of models included in each repository, the primary difference between CMIP3 and CMIP5 is in the future scenarios used. CMIP3 simulations are based on the emission scenarios developed in the 1990s, referred to as SRESs (Nakicenovic et al. 2000). CMIP5 simulations are based on the RCP scenarios described in Section 2.1.1.

The third through seventh columns of Table 3 list datasets generated by various empirical downscaling methods that are widely used by the climate impact community. Some are available as a data product from either the developer or from a data server (e.g., WorldClim); others are software packages that require the user to perform the calculations to generate the required output (e.g., CDFt [Vrac and Michelangeli 2012]). The tenth through twelfth columns list available or soon-to-be-available high-spatial-resolution dynamically downscaled output. NARCCAP was produced using one SRES A2 scenario, and 50-km resolution and is widely used. CORDEX is a planned successor to NARCCAP; its spatial resolution varies from 50 to 25 to 10 km, and is currently a work in progress. The SERDP downscaling product is available at 12-km spatial resolution using two RCP scenarios. Some details of the type of technique, output formats, and time and spatial resolutions are listed in the top half of Table 3. It is always best to refer to the original data source to confirm details and obtain further details; many of these datasets are frequently updated and modified.

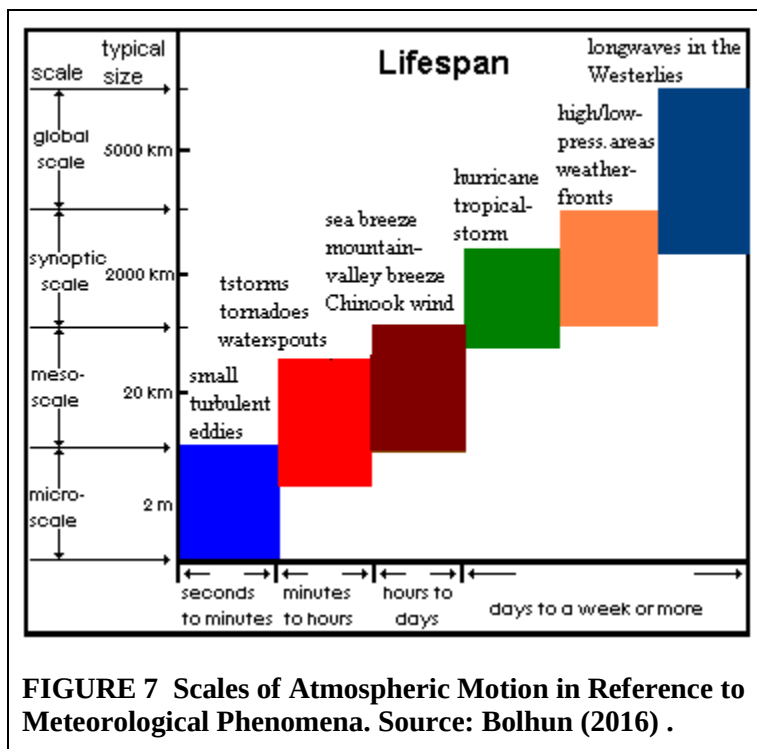
In the second half of Table 3, we attempt to provide some preliminary guidelines for the application of these datasets to answer a particular question. The first row describes the further processing of the data that may be necessary before it will be suitable for use in an application. The most significant of these adjustments is adjusting the data to account for calculated differences between the model output and historical weather datasets (referred to as bias in the downscaling community). Most empirical downscaling method (EDM) output is bias corrected and is ready to use. RCM-generated output is most often *not* bias corrected and thus a correction may be necessary before the output can be used. NARCCAP temperature and precipitation data soon will be bias corrected using the KDDM approach and will be available at the NARCCAP website. Some effort will be required to collect climate data for a particular installation or region and to calculate the model bias from historical simulations performed by the model, which are generally included in these databases. Some recent RCM output uses bias correction *a priori* for

projections and may not need this adjustment; as before, please refer to the model data repository website for further clarification. The next three rows show the appropriateness of using a selected model output to obtain a selected climate variable or statistics. The appropriateness is color-coded; warm colors (red, yellow) are used to represent caution and green is used to express suitability of the model. This classification is based on the current state of knowledge and is qualitative in scope. We expect this to be a dynamic process, so the color assigned to a particular model/model output could change in the future. For example, the availability in the next decade or so of GCMs with spatial resolution of ~25 km could conceivably fill many of the needs listed here without the need for further downscaling.

4.3 REGIONAL DESCRIPTIONS OF CLIMATE AND CLIMATE MODELING CONSIDERATIONS

Each geographic region of the United States has its own unique climate characteristics that are determined by factors such as latitude, proximity to bodies of water, presence of complex terrain, and global atmospheric circulation patterns. Regional climate concerns are highly dependent on time of year because the nature of weather phenomena varies during the different seasons. Figure 7 shows the scales of atmospheric motion in relation to predominant weather phenomena. The main meteorological scales of interest in assessing regional weather and climate-related impacts in the United States are the synoptic scale (100 to 2,000 km) and the mesoscale (1 to 100 km). The mesoscale may be further subdivided into the coarse mesoscale (10 to 100 km) and the fine mesoscale (1 to 10 km), as indicated in Figure 7. For example, precipitation during the winter in the CONUS is mostly due to midlatitude cyclones on the synoptic scale, on the order of a 1,000 km in size. By contrast, precipitation during the summer occurs mostly in the form of smaller, more localized convective thunderstorms on the mesoscale. Spring and fall are transition periods when thunderstorms occur in association with midlatitude cyclones.

A very first important step to inform what type of downscaling tool is most appropriate for a particular place is to identify the specific meteorological phenomena that are most relevant to weather- and climate-related impacts. The relative importance of the physical representation of meteorology and climate in that place may be an important consideration in this endeavor. Dynamical downscaling is generally preferable if the underlying meteorological phenomena that drive climate-related impacts of interest occur on the mesoscale and if there is specific need to characterize precipitation extremes or other types of variables related to severe weather (e.g., wind gusts, flash flooding). Precipitation extremes associated with the most severe weather require atmospheric modeling on spatial scales on the order of a kilometer to explicitly represent thunderstorm-scale dynamics. At present, dynamical downscaling applications at this “convective-permitting” scale for climate impact assessment are mostly in the experimental research phase. However, it is possible to consider changes in the atmospheric environmental conditions in terms of thermodynamics and dynamics, to derive that from coarser-resolution model information, and to use this information to infer how severe weather phenomena will change (e.g., Trapp et al. 2007).



model performances when the bias can be attributed to a particular physical phenomenon in the model (see Figure 8 in Wang and Kotamarthi 2014). Some other biases related to spatial resolution (e.g., terrain and coastal regions) can be reduced by using models at higher spatial resolutions (e.g., Di Luca et al. 2012; Wang and Kotamarthi 2014; Wang et al. 2015).

Given the complexity of climate phenomena experienced over various parts of the United States, it would be difficult to come up with a set of recommendations that are region specific. Instead, in Table 4 we highlight aspects that may be useful to the reader and present a possible method for selecting models and model outputs based on the geography of the region of interest, in reference to meteorological scales in motion in Figure 7.

Table 4 describes the recommended use of downscaled model products for regions with specific geographic features. This table is not designed to specify which would be a “better” or “best” product to use, but rather to suggest the suitability of using a particular downscaled product as a function of meteorological scales of motion.

Evaluation of GCM outputs and downscaled projections provides some insights into the performance of these models over specific regions of the country (Mearns et al. 2012; Loikith et al. 2015; Pryor and Barthelmie 2013; Wang and Kotamarthi 2015). Generally speaking, coarse-grid GCMs generally underperform in simulating historical climate over highly variable terrain. Similarly, EDM underperforms over coastal regions, and RCMs underperform over the southwestern United States. As these model biases are identified, physics-based models (GCMs and RCMs) implement new parameterizations that improve the

TABLE 4 Recommendation Table on the Use of Climate Datasets based on Regional Features^a

Scale	Statistical Downscaling Methods						Dynamic Downscaling		GCM
	Delta Correction	Empirical Quantile Mapping	Bias correction	Parametric Quantile Mapping	Constructed Analogues	Wx generator	NARCCAP, CORDEX	Convective-permitting	CMIP5
Global scale: ~3,000 km or more, weeks to months (general circulation structure, jet stream position)									
Synoptic scale: 100–3,000 km, days to weeks (highs and lows, midlatitude cyclones, monsoons, atmospheric teleconnections)									
Course mesoscale- α , β : 10–100 km, hours to days (katabatic winds, weather fronts, mesoscale convective systems, tropical cyclones, sea breeze circulations)									
Fine mesoscale- γ : 1–10 km, hours to minutes (supercell thunderstorms, tornadoes, gust fronts, air mass thunderstorms, mountain-valley winds, mountain snowfall)									

^a In reference to meteorological scales of motion and phenomena in Figure 7.

4.3.1 Technical Terminology in Reference to Regional Climate Descriptions

The following technical meteorological and climate terms are relevant to one or more region discussed in the following sections. All terms are italicized where they occur in the regional descriptions:

- *Air mass thunderstorm*: Localized area of convective precipitation on the mesoscale. Develops with differential heating of land surface, for example due to the presence of mountains.
- *Arctic outbreak*: Onset of extremely cold temperatures, typically below 0°F. Occurs as an air mass from the polar region moves into the midlatitudes during the winter. May last several days to a week or more.
- *Atmospheric rivers*: Long streams of moisture in the lowest levels of the atmosphere that originate directly from the tropics and subtropics. Typically occur in association with extreme precipitation events, particularly on the west coast of the United States.

- *Atlantic Multidecadal Oscillation (AMO)*: Decadal variability in sea surface temperatures and climate patterns in the Atlantic basin.
- *El Niño Southern Oscillation (ENSO)*: Periodic warming of sea surface temperatures in the eastern tropical Pacific Ocean. Causes shifts in tropical rainfall across the entire Pacific basin and changes in atmospheric circulation patterns in the midlatitudes of both hemispheres.
- *Gust front*: Gust of wind that defines the leading edge of an outflow boundary of a thunderstorm.
- *Katabatic winds*: Downslope winds from mountains ranges or high plateaus.
- *Lake effect snow*: Narrow line of snowfall that occurs downwind of the Great Lakes, due to evaporation of warm water from the lake into a cold, dry airmass and formation of clouds as air rises and cools downwind of the lakes.
- *Madden Julian Oscillation*: Large eastward-propagating area of both intense and suppressed tropical rainfall that occurs in the Indian and Pacific Oceans and varies on a timescale of 60 to 90 days.
- *Mesoscale convective system*: Organized, isolated convective weather system that occurs during the warm season on the spatial scale of 10–100 km. Characterized by heavy precipitation and strong winds in its leading convective line lasting on the order of tens of minutes and followed by a period of relatively lighter precipitation lasting approximately several hours.
- *Microburst*: Sudden gust of wind due to a thunderstorm downdraft. Lasts on the order of minutes.
- *Midlatitude cyclone*: Synoptic-scale weather system that occurs in the midlatitudes, associated with fronts that define sharp spatial changes in temperature, moisture, winds, and precipitation. Typically has a lifetime of several days to a week.
- *Monsoon*: Regularly occurring wet period during the middle to latter part of the summer, with the majority of precipitation occurring due to thunderstorms.
- *Squall line*: Narrow band of heavy, convective precipitation and strong winds that typically occurs in association with the passage of cold front.
- *Straight-line winds*: Very strong winds (possibly exceeding hurricane force) that occur with the gust front of a squall line or mesoscale convective system.

- *Supercell thunderstorm*: Compact, rotating thunderstorm with a spatial scale of 1–10 km. Has a prolonged updraft that may result in hail or tornadoes. May last as long as several hours.
- *Tropical cyclone*: Very intense storm that forms over warm water, associated with extremely low pressure. Heavy rainfall occurs in bands around the core, or “eye,” of the storm. The most well-developed tropical cyclones with sustained winds exceeding 75 mph are referred to as hurricanes in the Atlantic Ocean, typhoons in the North Pacific Ocean, and cyclones in the South Pacific Ocean.
- *Tropical easterly wave*: Low-pressure trough that travels in an easterly direction in the tropics, associated with cloudiness and convective precipitation.
- *Warm sector*: In the structure of a midlatitude cyclone, the area ahead of cold front and behind a warm front. Convective thunderstorms in association with midlatitude cyclones are favored to occur in this sector.

4.3.2 Southwest, Including Coastal Southern California

Most of the Southwest United States experiences two seasonal maxima in precipitation. The cool season precipitation maximum comes from *midlatitude cyclones* that travel west from the Pacific Ocean. These produce regionally widespread precipitation, including snowfall in mountain ranges. The strongest winter precipitation events may tap *atmospheric rivers* from the subtropical Pacific Ocean. The hottest and driest time of year occurs in late spring to early summer (May through June), before the onset of the North American *monsoon*. During the time preceding the *monsoon*, the subtropical ridge that occurs directly over the region brings heatwaves that may exceed 110°F. During the North American *monsoon* in late summer (July through August), *air-mass thunderstorms* form in conjunction with the diurnal cycle of heating of the terrain. These may occasionally organize into *squall lines* and *mesoscale convective systems* on the most active convective days; these bring a greater proportion of precipitation to locations at relatively greater distance from mountain ranges (e.g., cities like Phoenix and Las Vegas). *Monsoon* severe weather dangers include heavy rain, flash flooding, *microbursts*, lightning, dust storms (haboobs), and hail. Lightning may also trigger wildfires, especially during the initiation phase of the *monsoon*. Although *tropical cyclones* do not impact the Southwest United States directly, on occasion the remnant lows of *tropical cyclones* that originate in the eastern tropical Pacific may cause widespread, heavy precipitation between late summer and early fall (August through October).

Of these phenomena, a model’s fidelity in reproducing *monsoons* is the most important factor in assessing the type of model dataset to use. ESDMs that are designed to produce daily output and use quantile mapping or constructed analogs for temperature and precipitation to the GCM output produce a dataset that is more representative for the region. RCM outputs also have less bias in simulating the precipitation over this region as compared to GCMs (e.g., Figure 2 in

Liang et al. 2006; Figure 4 in Kawazoe and Gutowski 2013; Wang and Kotamarthi 2015). Simple ESDMs such as delta, MBC, BCSD, SDSM, and EDQM may not be suitable for application over this region. In some instances, the assistance of an expert on climate in this region may be necessary to choose an appropriate dataset.

4.3.3 Great Plains

Midlatitude cyclones are the predominant weather phenomenon in the Great Plains during winter, producing regionally widespread precipitation including rain, snow, and ice storms. Blizzards are a particular danger because they produce high winds on the relatively flat terrain of the Great Plains. The most extreme cold occurs during *Arctic outbreaks*, when temperatures may fall well below 0°F. Severe weather associated with convection occurs during the transition seasons of fall and spring within the warm sector of maturing *midlatitude cyclones*. A unique combination of cold, dry air from Canada; warm, dry air from the Mexican Plateau; and warm, moist air from the Gulf of Mexico creates an atmospheric environment suitable for the development of *squall lines* and *supercell thunderstorms*. Late spring (April through May) is the time of year with maximum precipitation and danger from severe thunderstorms in the central Great Plains (Oklahoma, Kansas, Nebraska). The affected area shifts toward the northern Great Plains (South Dakota, North Dakota) in June and July. Particular dangers include strong tornadoes (Enhanced Fujita Scale [EF] level 3 and above), flash flooding, and hail. During summer, most precipitation occurs as a result of *mesoscale convective systems*. Although these systems typically are not associated with tornadoes, they can produce similarly damaging *straight-line winds* and heavy precipitation. The hottest and driest time of the year, and the time most likely to experience heatwaves exceeding 100°F, is typically mid- to late summer when the subtropical ridge is most likely to be directly overhead.

The Great Plains experience a wide variety of weather conditions and most models have difficulty reproducing *mesoscale convective systems*. Analysis of the GCMs participating in CMIP5 indicates that the models in general have a dry bias over this region for both summer and winter (Sheffield et al. 2013). Outputs from RCMs tend to have higher bias than GCMs over this region; as a result, some caution should be exercised in using these model outputs over this region, especially when the model representation of the clouds is based on parameterizations developed using observations, which is usually above 4-km grid resolution in RCMs. Sensitivity tests using 4 km with convective parameterization turned off show that the bias in precipitation can be reduced (Wang and Kotamarthi 2014). As shown in Tables 2 and 3, bias correction methods are employed by ESDMs to generate projected datasets over this region and generally provide reasonable results for the future projections. RCM output may need to be bias corrected before use in an application for a future time period.

4.3.4 Midwest

Midlatitude cyclones are the predominant factor in Midwestern weather. Similar to those in the Great Plains, these cyclones cause regionally widespread precipitation—mostly during fall, winter, and spring—including snow and ice storms. *Arctic outbreaks* with extremely cold

temperatures below 0°F are possible during the winter. Localized *lake-effect snowfall* may occur downwind of the Great Lakes (specifically Lake Superior, Lake Michigan, and Lake Erie) in conjunction with cold air outbreaks. The areas most influenced by these three lakes are on the northern side of Michigan's Upper Peninsula, on the western side of Michigan's Lower Peninsula, in northeastern Ohio, and in western Pennsylvania. Although thunderstorms in the Midwest tend not to be as severe as those in the Great Plains, more organized convection in the form of *squall lines*, *supercell thunderstorms*, and *mesoscale convective systems* can occur any time from late spring to early fall. Severe weather dangers associated with thunderstorms include flash flooding, tornadoes (although these typically are not as severe as those in the Great Plains), hail, lightning, and *straight-line winds*. Heatwaves exceeding 100°F can occur in mid- to late summer when the subtropical ridge is directly overhead.

GCM and RCM simulations have a fairly low bias over this region, although they do tend to have a dry bias over a region that includes the Great Plains and some of the Midwest (Sheffield et al. 2013). The eastern half of the Midwest generally shows a small wet bias in the winter and a dry bias in the summer in the CMIP5 models. RCMs tend to amplify these trends more than GCMs do. EDSM methods that employ bias corrections perform reasonably well over this region, as do more advanced EDSMs such as parametric quantile methods. No systematic evaluation of EDSM and RCM downscaling results have been performed for this region. Although the EDSM methods can provide a large ensemble of projections quickly, RCMs are necessary to provide climate variables beyond daily average temperature and precipitation and are often the only methods that provide enough data to understand precipitation and temperature extremes.

4.3.5 Northeast

Midlatitude cyclones are also predominant in the weather of the Northeast. These cause regionally widespread precipitation, mostly during fall, winter, and spring. A particular type of *midlatitude cyclone* in this region is the Nor'easter, in which an area of surface low pressure travels parallel to the coastline. This type of storm system produces widespread, heavy snow and/or possibly ice in the form of sleet and freezing rain, to the north and east of the surface low center. These *midlatitude cyclones* tend to be the strongest in the CONUS because they draw energy from the warm waters of the Gulf Stream off the East Coast. Arctic outbreaks with temperatures below 0°F occur during winter, often in association with Nor'easter events. Localized *lake-effect snowfall* may occur downwind of the Great Lakes (specifically Lake Erie and Lake Ontario) in conjunction with *Arctic outbreaks*. The most area most climatologically impacted by the lake is the western part of New York State in the vicinity of Buffalo, directly east of Lake Ontario. From spring to fall, most severe convective weather results from *squall lines* that form ahead of cold fronts. Although *supercell thunderstorms* and *mesoscale convective systems* can occur, these are typically weaker than those in the Great Plains and the Midwest. This results in comparatively less danger of strong tornadoes and *straight-line winds*. Heatwaves exceeding 100°F can occur in mid- to late summer, when the subtropical ridge is directly overhead. *Tropical cyclones* that originate in the Atlantic Ocean may affect the Northeast anytime during the *tropical cyclone* season (June through November). Although *tropical cyclones* that affect the Northeast are usually not classified as strong hurricanes (Category 3 and

above on the Saffir-Simpson scale), they can still be quite damaging if they are relatively slow moving, as Hurricane Sandy was. Coastal cities in the Northeast, especially New York City, are particularly vulnerable to storm surges from *midlatitude cyclones* such as Nor'easters and from *tropical cyclones*.

Analysis of the GCMs participating in the CMIP5 that includes Northeast, much of the Midwest, and the Southeast indicates that the models in general have a small dry bias over this region during winter, and small wet bias during summer (Sheffield et al. 2013). Surface temperature trends show a slight warm bias in both winter and summer. RCM results follow these trends and, as we indicate in Table 4, most datasets are appropriate after making necessary bias corrections.

4.3.6 Southeast and Gulf Coast

During the fall, winter, and spring, *midlatitude cyclones* are the predominant factor in weather in the southeastern United States. Depending on the location of a given event, various types of precipitation are possible, including widespread rain or frozen precipitation (snow, sleet, and freezing rain) and convective thunderstorms. Thunderstorms in the Southeast may include all forms of organized convection, *squall lines*, *supercell thunderstorms*, and *mesoscale convective systems*, and can produce dangerous heavy rain, flash flooding, hail, strong tornadoes, straight-line winds, and lightning. These dangers are maximized in mid- to late spring (March–April), prior to the season of most severe weather in the Great Plains. Compared to other regions in the eastern and central United States, the absolute amount of precipitation in the Southeast tends to be higher because more moisture is transported from the surrounding warm Atlantic Ocean and Gulf of Mexico. Heatwaves, during which temperatures may exceed 100°F for days, are possible anytime during the summer. Because of the relatively high humidity in the Southeast, measures of heat that account for the presence of atmospheric moisture (e.g., heat index) are more accurate than those based on temperature alone, in terms of quantifying their impact on human health and comfort. Of any region in the contiguous United States, the Southeast is most susceptible to the direct impacts of *tropical cyclones*, which can make direct landfalls along the entire length of the coastline from the Gulf Coast to the Eastern Seaboard. These tropical cyclones can be strong hurricanes (Saffir-Simpson scale of 3 and above), with attendant storm surge along the coast, strong winds, and heavy rainfall. Low-lying coastal cities in the Southeast are particularly vulnerable to tropical cyclones. New Orleans is probably the most vulnerable of all because of its low elevation and close proximity to multiple bodies of water that can inundate the city with storm surge, as illustrated by Hurricane Katrina in 2005.

RCM outputs do not have a definite bias toward either cold or warm temperatures over this region (Wang and Kotamarthi 2015); NARCCAP output has a cold bias for all the seasons and a higher spatial resolution simulation has a slight warm bias over this region. Precipitation is biased toward dry for all seasons from the RCMs. As we indicate in Table 4, most outputs are appropriate and a bias correction should be applied for temperature for further use in assessments. This region experiences severe weather from hurricanes, thunderstorms, and extreme heatwaves. The models (GCMs and RCMs) predict increasing storm intensity and more extensive heat waves. The incidence of hurricanes is also expected to increase. A limited number

of high-resolution GCMs (with 50 km or less grid resolution) in the CMIP5 repository can be used to estimate changes in hurricane frequency in the future for this region. Most RCM simulations do not cover the Atlantic and hence cannot provide any additional information beyond that available in the GCMs. EDSM methods are useful for evaluating mean trends over this region and do not have any particular skill beyond that of the GCM used for downscaling for extreme weather.

4.3.7 Mountain West

The climate of the Mountain West is heavily influenced by the presence of complex topography over a relatively large geographic area. The meteorological processes that lead to precipitation and severe weather are more terrain dependent than in other regions in the United States. During winter, precipitation is mostly associated with *midlatitude cyclones*. Mountain snowfall is caused principally by orographic lift in upslope flow, which cools the air to form clouds and precipitation. Downslope drainage flows and radiative cooling in high mountain valleys cause extreme low temperatures in winter, well below 0°F. Downslope *katabatic winds*—chinooks and boras—particularly on the east side of the Rockies, are prevalent during fall, winter, and spring. Winds during downslope windstorms can be quite severe, on rare occasions reaching hurricane force. During the period of the North American *monsoon* in late summer (July–September), similar to the Southwest, *air-mass thunderstorms* can form in association with the diurnal heating of the terrain and associated mountain-valley winds. Although these *air-mass monsoon thunderstorms* typically do not organize and are relatively localized to the areas where they develop, they present two unique dangers: (1) lightning and *microbursts*, the first of which may trigger wildfire and second of which may help spread it; and (2) heavy precipitation in steep terrain, which leads to severe flash flooding.

As expected, the primary driver of observed climate features over this region is the terrain. Higher-resolution RCM output would be the most appropriate to use.

4.3.8 Northwest/Pacific Coast

This area encompasses the Pacific coastal areas of Washington, Oregon, and northern California. A continental maritime climate, this region is one of the wettest in the United States. It experiences the majority of its precipitation in fall, winter, and spring in association with *midlatitude cyclones* from the Pacific Ocean. Pacific *midlatitude cyclones* cause widespread, steady precipitation when they occur. Severe weather associated with convective thunderstorms is a relatively rare occurrence, compared to other regions of the United States. Orographic lifting of air on the westward slope of the Cascade Range (Washington and Oregon) and the Sierra Nevadas (California) produces large amounts of snowfall in the mountains. The climate on the eastern, lee side of these mountain ranges tends to be much drier due to rain shadowing effects. The heaviest precipitation and most severe weather occurs when Pacific *midlatitude cyclones* access *atmospheric rivers*. During strong *atmospheric river* events along the Pacific coast, local precipitation typically is on the order of several inches of rain or more. Heavy precipitation can cause regionally widespread flooding and mudslides in steep terrain. The summer is typically the

hottest and driest time of the year, as the North American monsoon does not extend this far north. Heatwaves may occur with temperatures exceeding 100°F, especially in interior areas like the Central Valley of California that are well inland from the Pacific Coast.

This region's climate is dominated by both the influence of the ocean and complex terrain. RCM output will be appropriate for use in this region. One study of the CMIP5 model ensemble for the Pacific Northwest shows that the models in general produce all the observed features of climate over this region for the 20th century, with highest confidence in mean temperature and temperature-related statistics, and lower confidence in precipitation and precipitation-related statistics (Rupp et al. 2013). Similar biases can be expected to be present in the RCM output.

4.3.9 Pacific Islands Region

U.S. Pacific Island territories and military facilities are scattered throughout the Pacific Ocean. Because the weather and climate conditions of a particular island or archipelago depend largely on its geographic position within the ocean basin, sub-regions are considered separately, as described in the following sections. By far the greatest threat to small islands is sea-level rise (Nurse et al. 2014). Nurse et al. (2014) also recognized that the risks from climate change as they relate to small islands are not uniform for all the islands, and most of the risks arise from global changes and are not dependent on local changes. Here we focus on some of the specific weather phenomena that are more regional and global in scope and that have influence on small islands. The section concludes with a general overview of the applicability of high-resolution climate information to mid-ocean islands in general.

4.3.9.1 Hawaiian Islands and Midway Islands

These islands are situated in the central North Pacific in a zone of northeasterly trade winds. Little variation in temperature occurs throughout the year, and there is little year-to-year variability. Daily highs in coastal areas are in the range of 70 to 90°F and lows are in the range of 50 to 60°F. The largest Hawaiian Islands (Kauai, Oahu, Maui, and Hawaii) have distinct microclimates that occur due to the trade wind regime. In general, the northeastern or windward sides of the islands experience the greatest amount of precipitation and are densely vegetated with rainforests, whereas the southeastern, leeward sides experience the least precipitation and have more desert-like landscapes. The tops of the volcanoes at the center of the islands, for example Mauna Kea on Hawaii or Haleakalea on Maui, are higher than 10,000 feet above sea level; they are therefore much colder than coastal areas and may experience snow on occasion.

Two principal meteorological phenomena are triggers for severe weather on these islands. Extratropical *midlatitude cyclones*, known as Kona lows, occur mainly during winter and may cause heavy rainfall, flash floods, hail, high winds, and waterspouts. These occur about one to three times, on average, in a given year. Central Pacific hurricanes are rarer, but more damaging; they occur in summer and autumn and may directly impact the Hawaiian Islands on the order of once every 10 or more years. Central Pacific hurricanes tend to be stronger and more frequent in

El Niño years when central north Pacific sea surface temperatures are warmer than average. For example, Hurricane Iniki, a Category 4 hurricane on the Saffir-Simpson scale, which struck the island of Kauai in September 1992, was the most powerful storm ever recorded in the Hawaiian Islands.

4.3.9.2 Northern Mariana Islands and Guam

The climate in the Northern Mariana Islands and Guam is tropical wet/dry and the weather is generally hot and humid with little seasonal temperature variation. Daily average high temperatures are in the mid- to high 80s Fahrenheit and low temperatures in the mid-70s Fahrenheit. Most of the annual rainfall usually occurs during the wet season from July through November. Northeasterly trade winds are dominant throughout the year. Guam is located in the western North Pacific, which is one of the most active *tropical cyclone* areas of the world due to its proximity to the semi-permanent Mei-Yu front off the eastern coast of Asia during the rainy season. Frequent disturbances along the front account for heavy rainfall; these may occasionally intensify to tropical storm or typhoon status. An average of three tropical storms and one typhoon pass within 200 miles of Guam each year. Some may potentially reach super typhoon strength or the equivalent of Category 4 or 5 hurricanes on the Saffir-Simpson scale. Typhoons may occur anytime during the year, but the highest risk is in October and November.

4.3.9.3 Marshall Islands, Micronesia

Located in the central North Pacific, these islands have tropical wet/dry climates. The rainiest months occur in September and October during the passage of the Intertropical Convergence Zone (ITCZ). For example, monthly rainfall at Kwajelein Atoll in the Marshall Islands is approximately 12 inches during the wettest months and 4 inches during the driest months. Periods of heavy precipitation and inclement weather occur with organized tropical mesoscale convective systems. Variation of precipitation within the season is also related to the *Madden-Julian Oscillation*. *ENSO* (El Niño Southern Oscillation) is the principal factor in year-to-year climate variability; *ENSO*-related sea surface temperature changes are strongly linked to precipitation in the central North Pacific. Typhoons can occur in this part of the Pacific for islands located above approximately 5 degrees north latitude, but they are less frequent than in the northern Marianas and Guam.

4.3.9.4 American Samoa, South Pacific

Somewhat analogous to Hawaii, but in the southern hemisphere, American Samoa lies in a southeasterly trade wind regime. It experiences similar types of wet and dry microclimates as Hawaii, as a result of its terrain and the trade winds. *Tropical cyclones* may occur between November and May, and may be major (Category 3 or above on the Saffir-Simpson scale). South Pacific *tropical cyclones* in the vicinity of American Samoa tend to be more common during *El Niño* years.

4.3.10 Puerto Rico, Guantanamo Bay, and U.S. Virgin Islands

Puerto Rico and the U.S. Virgin Islands, along with the islands of Hispanola and Cuba, are part of the Greater Antilles chain of islands that ring the northeastern Caribbean Sea. These Caribbean islands have tropical wet/dry climates in a northeasterly trade wind regime, with warm and humid conditions year round. The dry season is during boreal winter, with the driest months being January and February. The wet season is from April to November. During the wet season a slight, but pronounced, decrease is present in precipitation during the early to mid-summer; this occurs in the Caribbean and the northern part of Central America, and is known as the mid-summer drought (or *canicula*, in Spanish). Periods of heavy precipitation with organized convection in the wet season occur due to tropical disturbances, principally *tropical easterly waves*. These disturbances may develop into tropical storms and hurricanes, and some of these may become major hurricanes (Category 3 and above on the Saffir-Simpson scale). Hurricane tracks differ though the course of the wet season. Cape Verde-type hurricanes, which originate off the western coast of Africa and traverse the tropical North Atlantic, can occur from July to September. Hurricanes from October to November tend to originate more in the central Caribbean Sea. Considerable year-to-year variability occurs in North Atlantic basin hurricane activity due to the *ENSO* and the *AMO*, which modify the background thermodynamic and dynamic conditions necessary for hurricane development.

Few RCM outputs have been generated over the Pacific Islands region (Lauer et al. 2013). For relatively large islands resolved by GCMs, the GCM output is the main choice for this region. If historical observational data exists for the islands, it may be possible to generate output using ESDMs for individual weather stations using point-based methods.

4.3.11 Alaska

The state of Alaska has diverse climate regimes that occur as a result of its physiogeography and latitude. Alaska has two major mountain ranges that extend from east to west. The Alaska Range is immediately north of the Pacific coast and includes Denali (formerly Mount McKinley), which is the highest point in North America. The Brooks Range is located near the Arctic Circle. Between these mountain ranges is Interior Alaska, defined as the Yukon River valley. This is a taiga, or evergreen forest region, of intermontane plateaus. To the north of the Brooks Range is the North Slope, a large coastal plain of mostly tundra that extends several hundred miles to the Arctic Ocean. Alaska also includes the Aleutian Islands, an archipelago that extends more than 1,000 miles south and west of the North American continental landmass. Owing to its high northern latitude, Alaska generally experiences a period of constant daylight during the summer and constant darkness during the winter. This effect is most extreme in Barrow, the northernmost city in Alaska, which is located on the North Slope north of the Arctic Circle. Barrow has 24 hours of sunshine every day from early May to the beginning of August and 24 hours of darkness every day from late November to near the end of January.

The area south of the Alaska Range to the Pacific Ocean, including the cities of Anchorage and Juneau, is a wet and cold maritime climate. Most of this precipitation comes from Pacific *midlatitude cyclones* that are climatologically favored to occur in association with

the semi-permanent Aleutian Low in the North Pacific Ocean. Heavy rain and snow are possible with the passage of these midlatitude cyclones; the wettest period is in late summer and early autumn. Precipitation near the Pacific Coast may exceed 100 inches per year, on average. The strongest *midlatitude cyclones* may cause winds near to or greater than hurricane force; this is a particular concern in areas of the Aleutian Islands. The permanent snow line in the Alaska Range is at an elevation of approximately 5,200 feet.

Interior Alaska, on the northern lee side of the Alaska Range, experiences a comparatively much more arid, continental climate. For example, the city of Fairbanks, in the Yukon River Valley, receives approximately 10 inches of precipitation per year and approximately 40–45% of this precipitation is in the form of snow. Interior Alaska experiences large seasonal temperature differences compared to the contiguous United States, with a mean annual summer temperature (July) of nearly 70°F and a mean annual winter temperature (January) of 20°F. The recorded temperature extremes range from -60°F to 100°F. The coldest temperatures in Interior Alaska occur in association with temperature inversions near the surface in winter in valleys, due to radiative cooling and downslope drainage flows in clear, calm conditions. The North Slope is approximately as dry as Interior Alaska, but daily temperatures rarely exceed the freezing level there. The North Slope is comparatively windier, on average, than Interior Alaska, because a lack of terrain fails to impede air flows from the Arctic Ocean and cause temperature inversions and drainage flows.

Alaska experiences extreme weather most of the year. Several downscaled datasets for this region have been produced using both ESDM and RCMs. An evaluation of the CMIP3 GCM output from 15 separate models found that the models that show the best performance over this region are the same as the ones that perform best for various other regions of the globe (Walsh et al. 2008). An evaluation of 17 simulations from CMIP5 reveals a positive tendency for precipitation over winter and on average a negative tendency for precipitation in summer (Sheffield et al. 2013). Surface temperatures are similarly biased, with a small negative bias for winter and a small positive bias during summer, both with large standard deviations. Unfortunately, no comprehensive evaluation has been conducted of the different dynamic downscaling methods over this state other than to recognize that population centers in the state are close to the coast and dominated by rapidly changing terrain features. This suggests caution should be used when using raw coarse grid GCM output without bias correction. Simple ESDM methods such as the delta method seem to be preferred by local planners who use the GCM output for the state and local communities (SNAP 2016). The SNAP dataset provides monthly mean delta corrected projections for large number of CMIP5 model scenarios. The dataset is not designed for use to study extremes in precipitation or temperature and is limited by the use of delta method, as already described (Table 1). The RCM outputs over this region need further evaluation, and available output should be used with bias corrections.

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