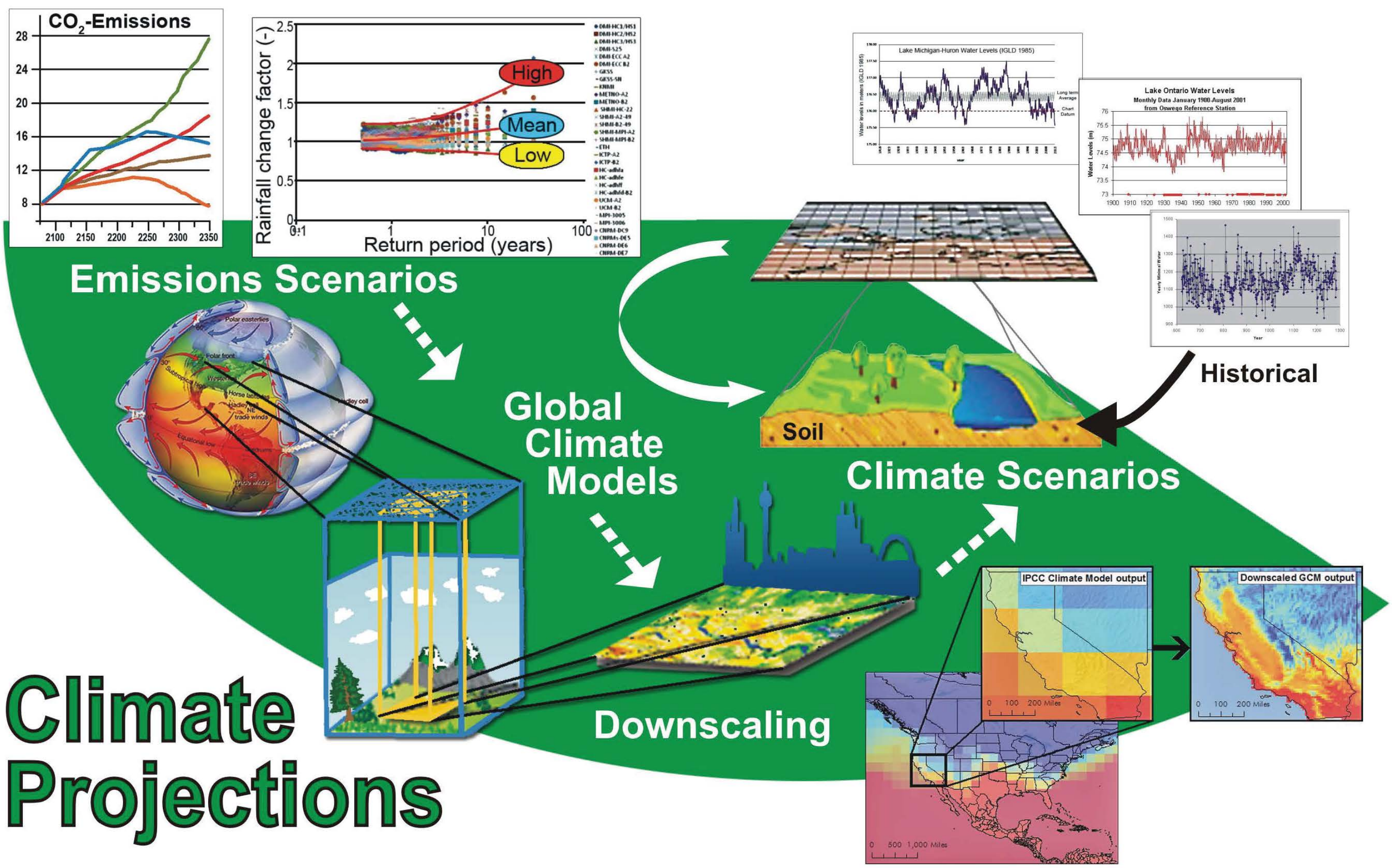
RECLAMATION

Managing Water in the West

Considerations for Selecting Climate Projections for Water Resources, Planning, and Environmental Analyses



U.S. Department of the Interior
Bureau of Reclamation
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Mission Statements

The U.S. Department of the Interior protects America's natural resources and heritage, honors our cultures and tribal communities, and supplies the energy to power our future.

The mission of the Bureau of Reclamation is to manage, develop, and protect water and related resources in an environmentally and economically sound manner in the interest of the American public.

Considerations for Selecting Climate Projections for Water Resources, Planning, and Environmental Analyses

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Contents

Figures

Tables

Acronyms and Abbreviations

°C	degrees Celsius
°F	degrees Fahrenheit
AOGCM	Atmosphere-Ocean General Circulation Models
AR4	IPCC Fourth Assessment Report
AR5	IPCC Fifth Assessment Report
ARRM	Asynchronous Regional Regression Model
BCCA	Bias Corrected and Constructed Analogue
BCSD	Bias Corrected and Spatially Disaggregated
CDF	cumulative distribution function
CIRC	Climate Impacts Research Consortium
CMIP2	Coupled Model Intercomparison Project Phase 3
CMIP3	Coupled Model Intercomparison Project Phase 3
CMIP5	Coupled Model Intercomparison Project Phase 5
CONUS	Continental United States
CPC	Climate Prediction Center
Department	Department of the Interior
D&S	Reclamation Manual Directives and Standards
DTR	diurnal temperature range
EDCDFm	Equidistant Quantile Mapping
ENSO	El Nino Southern Oscillation
ESM	earth system model ETevapotranspiration
GCM	global climate model
GMFD	Global Meteorological Forcing Dataset
IAM	integrated assessment model in/dayinches per day
IPCC	Intergovernmental Panel on Climate Change
K	Kelvin
$kg/m^2/s$	kilograms per meter squared per second, approximately equal to mm per second for liquid water
km	kilometer
LCC	Landscape Conservation Cooperatives
MACA	Multivariate Adaptive Constructed Analogues
MAGICC	Model for the Assessment of Greenhouse-gas Induced Climate Change
m	meter
mm	millimeter
m/s	meter per second
METDATA	University of Idaho Gridded Surface Meteorology Dataset
NASA	National Aeronautics and Space Administration
NARCCAP	North American Regional Climate Change Assessment Program
NCAR	National Center for Atmospheric Research
NCEP	National Center for Environmental Prediction
NEPA	National Environmental Policy Act
NEX-GDDP	NASA Earth Exchange Global Daily Downscaled Projections
NKN	Northwest Knowledge Network
NOAA	National Oceanographic and Atmospheric Administration
NWS	National Weather Service
Pa	pascals
PCMDI	Program for Climate Model Diagnostics and Intercomparison
PRISM	Parameter-elevation Relationships on Independent Slopes Model
RCM	regional climate models
RCP	representative concentration pathway
REACCH	Regional Approaches to Climate Change – Pacific Northwest Agriculture
Reclamation	Bureau of Reclamation
SECURE	
Water Act	The Omnibus Public Land Management Act of 2009 (Public Law 111-11) Subtitle F
S&T	Science and Technology
SRES	Special Report on Emission Scenarios
SST	sea surface temperature
TAR	IPCC Third Assessment Report
UNFCCC	United Nations Framework Convention on Climate Change
USGS	U.S. Geological Survey
W/m^2	Watts per meter squared
WaterSMART	Sustain and Manage America's Resources for Tomorrow
WCRP	World Climate Research Program
WMO	World Meteorological Organization
WWCRA	West-wide Climate Risk Assessment

Executive Summary

For over a century, Reclamation's mission has focused on managing water resources in the Western United States. Water resources, planning, and environmental studies carried out to support Reclamation's mission have routinely considered hydrologic variability, including variability of water supplies and demands from season to season and year to year. Because weather and climate are two of the primary drivers of water supply and demand, Reclamation studies have also routinely considered weather and climate variability. The SECURE Water Act directs Reclamation to evaluate the risks and impacts of climate change in long-range planning and decision making (see Section 1.1. of the main report), including:

- Water resources and environmental analyses
- Planning studies
- Design and analysis of current and proposed infrastructure and operating plans

Considering climate change involves analyzing projected changes in weather and climate conditions as well as the effects of these changes on water supplies, demands, and management.

This document provides an overview of the primary considerations relevant to selecting climate projection information for use in a given water resources, planning, or environmental analysis.

Audience

For *technical specialists* involved in selecting and using climate projections for a given study—e.g., climatologist, hydrologists, and water resources engineers—this document provides a brief overview of the models and methods used to develop climate projections (Section 2.) and relevant considerations for selecting an appropriate climate projection dataset and set of climate projections to meet their specific study objectives (Section 3.). This document also provides a detailed summary of available climate projection datasets (Section 4.) and established methods for selecting climate projections for use in a detailed analysis (Section 5.).

For *other study team members* involved in interpreting and documenting the use of climate change information in a given study—e.g., planners, environmental specialists, and resource managers—this document provides an overview of how climate projections are developed (Section 2.) and the choices and considerations involved in selecting climate projections for analysis in the study (Section 3.).

Understanding Climate Projections

Section 2. of this document provides an overview of the models, methods, and assumptions used to develop climate change projections and to incorporate climate projections into subsequent analyses of future water supplies and demands and environmental conditions. *Technical specialists* involved in selecting and using climate projections need a firm understanding of how climate projections are developed by the scientific community in order to select, interpret, and apply climate projection information to support water resources, planning, and environmental analyses. In addition, *other study team members* should have a basic understanding of how climate projections are developed and used in order to accurately interpret and document climate change information used in a given study. Team leads and all team members also need to be able to effectively consider and communicate climate change results within the overall study and decision-making context.

Selecting Climate Change Information

Section 3. of this document summarizes key questions and considerations for study teams when selecting climate projection information for a given study. The scientific community has developed a vast amount of information regarding projected climate change, including several large datasets of climate projections based on different models, methods, and assumptions. In many cases, these datasets contain a large number—in some cases several hundred—of global or regional climate projections. To consider risks and impacts from climate change, study teams must choose an appropriate source of climate change projections for their study. This typically consists of two inter-related choices:

1. Selecting an appropriate **climate projection dataset** (or datasets) to serve as the basis for considering climate change.
2. Selecting a **set of the climate projections** from the chosen dataset for detailed analysis in support of the study objectives.

Study teams must consider a number of factors when selecting a climate change projection dataset. Should we use projections from the CMIP3 Multi-Model Dataset, the CMIP5 Multi-Model Dataset, or a combination of both? Should we use GCM projections directly or should we use downscaled projections? How should we select an appropriate set of projections for detailed analysis?

Section 3. of this document discusses key questions and considerations in selecting climate projection information. This section will help technical specialists to understand and consider these relevant factors in selecting climate projection information. In addition, this section will help general team members to understand these relevant factors in order to characterize and document the selection of climate projection information used in the study.

Climate Projection Datasets and Climate Projection Selection Methods

Sections 4. and 5. of this document provide *technical specialists*—e.g., climatologists, hydrologists, and water resources engineers—with a concise summary of available climate projection datasets and established methods for selecting a set of climate projections from a given dataset for detailed analysis. Section 4. of this document briefly describes several existing global and regional climate projection datasets that study teams may choose as the basis for analyzing potential risks and impacts from climate change. Section 5. then summarizes two broad classes of methods for selecting a set of climate projections from a given climate projection dataset for detailed analysis in support of a given study. These sections also provide references where technical specialists can go for more detailed information. In addition, these sections also provide general team members with an overview of key information regarding available climate projection information resources.

1. Introduction

For over a century, the Bureau of Reclamation's (Reclamation) mission has focused on managing water resources in the Western United States. Water resources, planning, and environmental studies carried out to support Reclamation's mission have routinely considered hydrologic variability, including variability of water supplies and demands from season to season and year to year. Because weather and climate are two of the primary drivers of water supply and demand, Reclamation studies have also routinely considered weather and climate variability. Since 2009, Reclamation is now required to consider and analyze risks and impacts from climate change in long-range planning and decision making (see Section 1.1). Considering climate change involves analyzing projected changes in weather and climate conditions as well as the effects of these changes on water supplies, demands, and management.

The scientific community has developed a vast amount of information resources regarding projected climate change, including several large datasets of climate projections based on different models, methods, and assumptions. In many cases, these datasets contain a large number—in some cases several hundred—of global or regional climate projections.

When conducting a quantitative analysis of the potential impacts of climate change, study teams must choose an appropriate source of climate change information to support their specific study objectives. This typically consists of two inter-related choices:

1. Selecting an appropriate **climate projection information resource** (i.e., dataset or datasets) to serve as the basis for considering climate change

2. Selecting a **set of the climate projections** from the chosen dataset for detailed analysis in support of the study objectives.

Selection of an appropriate climate projection dataset and selection of a set of climate projections for detailed analysis are commonly carried out by the technical specialists on a given study team. *Technical specialists* involved in selecting and using climate projections—e.g., climatologist, hydrologists, and water resources engineers—should have a detailed understanding of available climate projection datasets, the models and methods used to develop these datasets, and relevant considerations for selecting an appropriate climate projection dataset and set of climate projections to meet their specific study objectives.

In addition to these technical specialists, *other study team members* who are not directly involved in selecting and using climate projections—e.g., planners, environmental specialists, and resource managers—should have a general understanding of how climate projections are developed and the choices and considerations involved in selecting climate projections in order to accurately interpret and document the information and methods used in the study.

This document provides an overview of the primary considerations relevant to selecting climate projection information for use in a given water resources, planning, or environmental analysis. The information in this document is intended to help study teams make well-informed decisions regarding selection of climate projection information to inform water resources and environmental planning. The purpose of this document is not to provide guidance regarding selection of climate projections for a given study, but instead to provide an overview of relevant considerations and a concise summary of available climate projection datasets and established methods for selecting a set of climate projections for use in a given study.

1.1. Requirements for Analyzing Climate Change

The Omnibus Public Land Management Act of 2009 (Public Law 111-11) Subtitle F, referred to as the SECURE Water Act, directs Reclamation to evaluate the risks and impacts of climate change in each of eight major Reclamation river basins identified in the Act. The act also authorizes Reclamation to work with non-Federal partners to develop and evaluate adaptation and mitigation strategies to address potential water shortages, conflicts, and other impacts from climate change.

As stated above, in addition to the SECURE Water Act, The Department of the Interior's (Department) Secretarial Order 3289 requires that "*each bureau and office of the Department must consider and analyze potential climate change impacts when undertaking long-range planning exercises, setting priorities for scientific research and investigations, developing multi-year management plans, and making major decisions regarding the potential use of resources under the Department's purview*." Building on this order, Departmental Manual 523 DM 1 states that:

> *"The Department will use the best available science to increase understanding of climate change impacts, inform decision making, and coordinate an appropriate response to impacts on land, water, wildlife, cultural and tribal resources, and other assets. The Department will integrate climate change adaptation strategies into its policies, planning, programs, and operations, including, but not limited to, park, refuge, and public land management; habitat restoration; conservation of species and ecosystems; services and support for tribes and Alaska Natives; protection and restoration of cultural, archeological and tribal resources; water management; scientific research and data collection; land acquisition;*

management of employees and volunteers; visitor services; construction; use authorizations; and facilities maintenance."

Further direction for a climate change adaptation program comes from Executive Order 13653 (November 1, 2013), which lays out new policy directives for Federal agencies to, "…prepare the Nation for the impacts of climate change by undertaking actions to enhance climate preparedness and resilience…" The Executive Order includes direction for agencies to modernize Federal programs to support climate resilient investments and manage land and water resources for climate preparedness and resilience.

To implement Department Policy 523 DM 1, Reclamation updated its Reclamation Manual with a new Directive and Standard (D&S) for Water and Related Resources Feasibility Studies (CMP 09-02)[1] on July 1, 2015. This D&S outlines the process by which Reclamation conducts feasibility studies. Specifically, the D&S states that "potential impacts of climate change will be considered when developing projections of environmental conditions, water supply and demand, and operational conditions at existing facilities as part of the without-plan future condition"[2] (CMP 09-02 section 7.H.2.f). The D&S also directs climate change impacts to be further analyzed if "*there is a reasonable likelihood of significant variation in hydro-climatic conditions over the planning horizon, between alternatives, or both; and regional models have been down-scaled to a resolution adequate for the study area, or can be produced within a reasonable time and cost constraints*" (CMP 09-02 section 7.H.2.f (i) and (ii)).

1.2. Reclamation Activities to Address the Effects of Climate Change

To meet the needs for affordable water and power in the West, protect the water-related environment, and meet trust obligations to tribes, Reclamation must become more resilient to the impacts of climate change and variability, including severe floods and droughts.

Meeting Reclamation's mission in the face of changing climate conditions will require continued emphasis on successful, ongoing efforts, as well as consideration of climate change in areas where it has not been fully considered in the past, such as in decisions regarding ecosystem restoration, reservoir operations, and infrastructure investments.

Reclamation is taking actions to address the impacts of climate change by working with our partners in river basins across the West to incorporate climate change projections

[1] http://www.usbr.gov/recman/cmp/cmp09-02.pdf

[2] The without-plan future condition is also termed the "Forecast Future Condition" and is defined in CMP 09-02 as, "Characterizing future conditions without the proposed Reclamation action, including actions that may be expected or anticipated by others."

into relevant aspects of Reclamation's mission. General information on Reclamation's climate change programs is available at http://www.usbr.gov/climate. Reclamation activities to address climate change are being implemented through a combination of three primary approaches:

- **Collaborative Climate Change Impact and Adaptation Studies.** See the WaterSMART Programs at http://www.usbr.gov/watersmart.
- **Planning and Related Environmental Compliance.** See Reclamation's technical guidance at http://www.usbr.gov/watersmart/wcra.
- **Research and Development Activities**. See the Research and Development Office's climate website at http://www.usbr.gov/research/climate.

1.2.1. Collaborative Climate Change Impact and Adaptation Studies

The Department of the Interior's WaterSMART (Sustain and Manage America's Resources for Tomorrow) Program, is a key component of Reclamation's implementation of a climate change adaptation program. The WaterSMART Program follows a tiered approach that includes:

- **West-Wide Climate Risk Assessments (WWCRA)**. These assessments encompass a variety of activities aimed at developing baseline information regarding the risks and impacts of climate change to water supplies and demands in Reclamation's river basins, including conducting impact assessments to evaluate climate change impacts to Reclamation's mission. See http://www.usbr.gov/watersmart/wcra/index.html.
- **Basin Studies.** These in-depth water supply and demand analyses are selected through a competitive proposal process and are cost shared between Reclamation and local stakeholders. Through the Basin Studies, Reclamation works collaboratively with stakeholders to evaluate current and future water supplies and demands, system reliability, and adaptation and mitigation strategies to address current and projected imbalances between water supply and demand. See http://www.usbr.gov/watersmart/bsp/index.html.
- **Landscape Conservation Cooperatives (LCC)**. LCCs are partnerships of governmental (Federal, State, tribal, and local) and non-governmental entities and are an important part of the Departments efforts to coordinate climate change science efforts and resource management strategies. See http://www.usbr.gov/watersmart/lcc/ for more information on Reclamation's participation in LCCs.

These activities are complementary and represent a multi-faceted approach to assess climate change risks to water supplies and impacts to activities in Reclamation's mission, as well as the development of adaptation strategies to meet future water demands.

1.2.2. Planning and Related Environmental Compliance.

A variety of planning efforts and related environmental compliance are incorporating climate change considerations. Reclamation has issued guidelines for incorporating climate change information into water resources planning studies and environmental compliance studies conducted under the National Environmental Policy Act (NEPA):

- Reclamation 2014 (Technical Guidance).[3] Technical Guidance for Incorporating Climate Change Information into Water Resources Planning Studies and plans to continue issuing guidance http://www.usbr.gov/watersmart/wcra/docs/WWCRATechnicalGuidance.pdf

- Reclamation 2014 (Adaptation). Climate Change Adaptation Strategy http://www.usbr.gov/climate/docs/ClimateChangeAdaptationStrategy.pdf.

- Reclamation 2012. Reclamation's NEPA Handbook, Section 11.7 Climate Change. http://www.usbr.gov/nepa/docs/NEPA_Handbook2012.pdf

Reclamation continues to develop strategies and guidance to support consideration of climate change throughout its mission. Information on guidance and updates is available at http://www.usbr.gov/watersmart/wcra/.

1.2.3. Research and Development Activities

Reclamation's Science and Technology (S&T) Program is leading development of the data and tools necessary to support climate change adaptation by Reclamation, and its customers and stakeholders. The S&T Program is a Reclamation-wide competitive, merit-based applied research and development program that focuses on developing innovative solutions to water and power challenges in the Western United States. Climate change and variability is an S&T Program priority area, and S&T projects have developed improved methods to develop and use climate change and variability information for a variety of water resources planning and applications. For a list of research projects, go to the S&T Program project website (http://www.usbr.gov/research/projects/search.cfm) and search for the keyword "climate."

[3] Parentheses after a citation differentiate references from the same entity in the same year.

In addition, through the S&T Program, Reclamation has led a partnership of eight Federal, academic, and non-governmental organizations to provide future projections of temperature, precipitation, and streamflow throughout the contiguous United States (CONUS) to support locally relevant decision making (see http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/). Reclamation's Research Office also supports a variety of cooperative agreements and collaborative research efforts with universities, research centers, and other Federal agencies focused on developing and applying climate projection information for water resources planning and management.

1.3. Purpose of This Document

This document provides Reclamation study teams with a concise summary of available climate projection information resources, as well as established methods to select a subset of climate projections for detailed analysis to support a specific study.

The purpose of this document is to provide study teams with an overview of the primary considerations relevant to selecting appropriate climate change information for use in a given water resources, planning, or environmental analysis. This document also provides a concise summary of existing climate projection datasets and established methods for selecting a set of climate projections from a given dataset for detailed analysis.

As part of WWCRA, Reclamation recently developed technical guidance for incorporating climate change information into water resources planning studies (Reclamation 2014 [Technical Guidance]). This technical guidance was developed to assist study teams in determining an appropriate level of climate change analysis and identifying a specific method for incorporating climate projections into a given study. However, the guidance does not address how to select a climate projection dataset to serve as the basis for considering climate change and how to select a set of climate projections from the chosen dataset for detailed analysis. This document is intended to provide study teams with the information needed to make informed decisions regarding selection of climate projection information to support water resources, planning, and environmental analyses. However, this document does not provide direct guidance regarding selection of climate projections for any given study.

This document is intended for Reclamation study teams, including *technical specialists* involved in selecting and using climate projections—e.g., climatologist, hydrologists, and water resources engineers—as well as *other study team members* involved in interpreting and documenting study data, methods, and results—e.g., planners, environmental specialists, and resource managers.

This document is organized into five sections:

- Section 1 (this section) provides an introduction to this document, including an overview of orders, directives, and legislation detailing Reclamation's requirements and responsibilities with respect to considering and analyzing climate change impacts; a summary of Reclamation activities to address the effects of climate change; and a summary of the purpose and organization of this document.

- Section 2 provides a brief introduction to the models and methods used to develop climate projection information, including an overview of global climate models (GCM), emissions scenarios and representative concentration pathways (RCP), and downscaling methods.

- Section 3 provides discussion of key questions and issues related to selecting an appropriate climate projection dataset and selecting a subset of projections to be incorporated into detailed analysis in support of a specific study.

- Section 4 describes several widely used climate projection datasets, including multi-model datasets of climate projections derived from global[4] and downscaled GCM simulations.

- Section 5 summarizes commonly used methods for selecting subsets of climate projections for use in a detailed analysis in a given study along with their potential strengths and weaknesses in the context of water resources and environmental planning.

Sections 2 and 3 of this document provide all study team members an overview of how climate projections are developed and the choices and considerations involved in selecting climate projections for a given study. These sections are intended primarily to help planners, environmental specialists, resource managers, and *other study team members* with a general understanding of climate projections in order to facilitate interpreting and documenting study data, methods, and results. Sections 4 and 5 provide *technical specialists* with a concise summary of existing climate projection datasets and an overview of established methods for selecting climate projection information for use in a given study.

[4] Throughout this document, the terms *global GCM simulation* and *global projection* refer to GCM outputs at the original GCM spatial resolution, without any downscaling or bias correction applied.

2. Overview of Models and Methods Used to Develop Climate Projections

This section provides a general overview of how climate projections are developed, along with a brief summary of how climate projections are incorporated into hydrology and resource models to evaluate impacts of projected climate change on water and environmental resources. This section also defines key terms and concepts related to climate, climate change, and climate projections.

The purpose of this section is to provide planners, environmental specialists, resource managers, and other study team members with a general understanding of how climate projections are developed in order to facilitate interpreting and documenting study data, methods, and results. This section does not provide a detailed or comprehensive technical discussion of the data, models, and methods used to develop and apply climate projections to support water resources, planning, and environmental analyses.

The process of developing and applying climate projection information is illustrated schematically in Figure 1. In the context of water resources and environmental management, planners, resource managers, and decision makers identify the decisions to be made and the information required to support those decisions. Study teams, including *technical specialists*, develop the data, models, and decision support tools to evaluate relevant conditions and alternatives. Where decisions require information on future climate, hydrologic, and environmental conditions—e.g., future water supplies and demands, habitat conditions, and relevant factors—study teams must also select relevant climate projections and incorporate climate projections into relevant data, models, and decision support tools.

Climate projections typically are not developed as part of an individual water resources, planning, or environmental analysis. Rather, the scientific community has developed a vast amount of information regarding projected climate conditions, including multiple datasets of global and regional climate projections (see Section 4). These datasets constitute the climate projection information available to Reclamation study teams. While climate projections are not developed to meet the specific needs of a given study, the scientific community has developed climate projections in part to meet the general decision needs of decision makers, including water and environmental resource managers. The technical specialists on a given study team must select an appropriate set of climate projections to support their study needs and incorporate those projections into relevant data, models, and decision support tools.

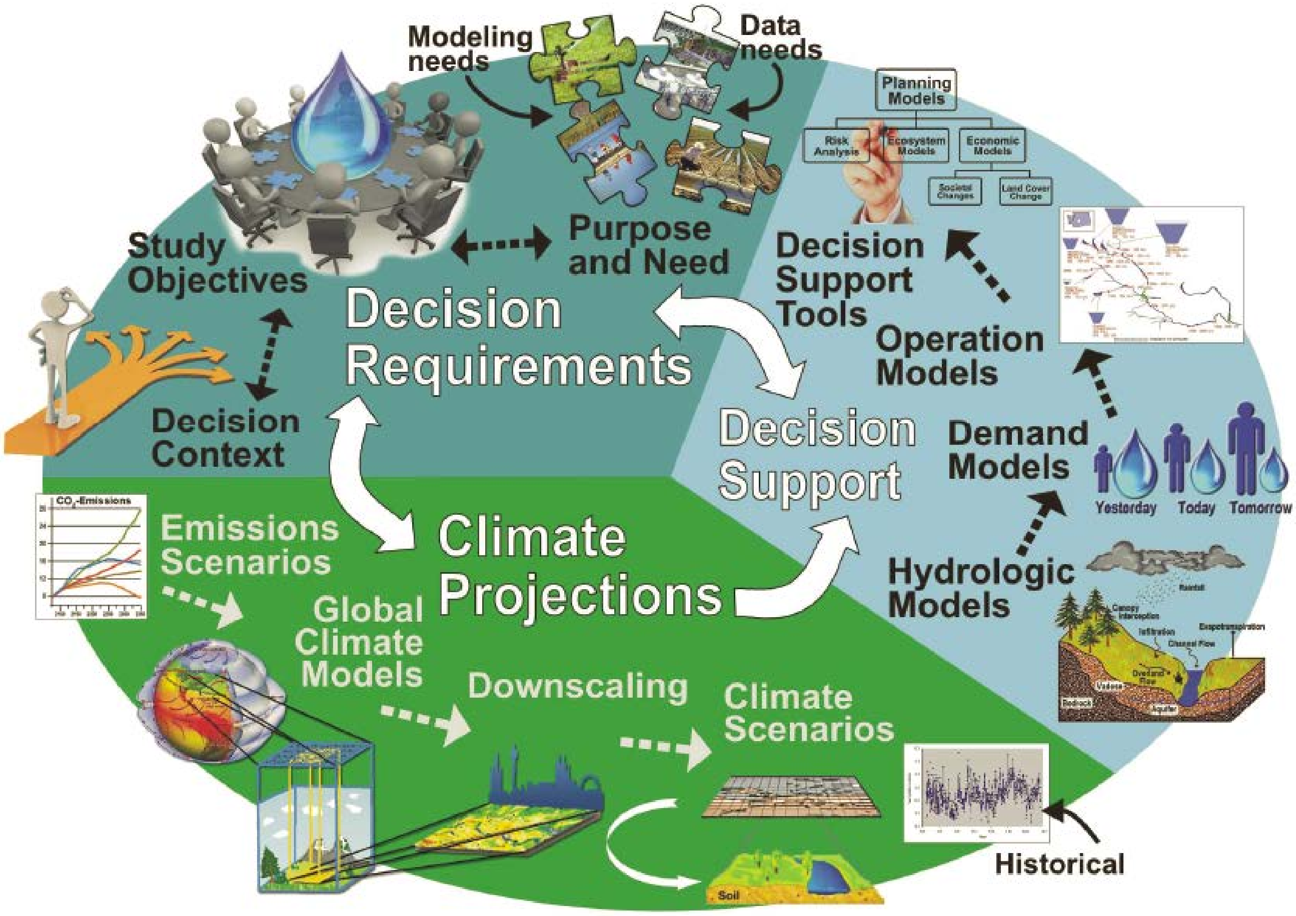

Figure 1: Schematic overview of steps required to develop projections of future climate and to incorporate climate projection information into modeling and analysis to support water resources and environmental planning, management, and decision making.

- Section 2.1 provides an overview of the steps required to develop projections of future climate and to incorporate climate projection information into subsequent modeling and analysis of water and environmental resources.

- Section 2.2 introduces and defines key concepts related to climate, climate change, and climate projections.

- Section 2.3 discusses how climate projection information is incorporated into subsequent modeling and analysis of water and environmental resources.

2.1. Key Terms and Concepts

Understanding, interpreting, and documenting climate projections and their use in water resources, planning, and environmental analyses requires study teams to clearly understand key terms and concepts related to climate. In particular, study teams should understand the distinctions between weather and climate, as well as between climate variability and climate change. Study teams should also understand the concepts of stationarity and non-stationarity as they relate to climate variability and climate change, and to study assumptions regarding future climate conditions.

The term *weather* is generally used to describe the state of the atmosphere at a specific place and time, including characteristics such as temperature, precipitation, wind speed, and humidity. Weather typically refers to the day-to-day conditions directly experienced by humans and the environment, including rain storms and heat waves. The term *climate*, on the other hand, is generally used to describe the long-term average weather conditions over a given region. In general, climate describes "normal" conditions for a given place at a given time of year, while weather describes "actual" conditions for that place at a specific date and time. In other words, "Climate is what we expect; weather is what we get" (Heinlein 1973).

The World Meteorological Organization (WMO) defines the term *climate variability* as "variations in the mean state and other statistics of the climate [such as standard deviations, the occurrence of extremes, etc.] on all temporal and spatial scales, beyond individual weather events" (WMO 2015). By contrast, WMO defines *climate change* is defined as "a statistically significant variation in either the mean state of the climate or in its variability, *persisting for an extended period* (typically decades or longer)" (WMO 2015; emphasis added). In other words, *climate variability* refers to year-to-year changes in climate conditions, whereas *climate change* refers to long-term trends in climate that persist for multiple decades or longer. For example, year-to-year variations in annual rainfall over a given region represent climate variability, whereas a significant trend in annual rainfall over a fifty-year period represents climate change. Climate change is thus typically distinguished from climate variability by the timescale being considered.

Both climate variability and climate change may occur due to natural processes or due to anthropogenic (human-caused) activities (WMO 2015). Climate variability on timescales from years to a few decades, however, is driven overwhelmingly by natural processes. Natural processes that contribute to climate variability include internal atmospheric dynamics, as well as coupled interactions between quickly-varying atmospheric dynamics and slowly-varying components of the earth system such as ocean circulation and temperature patters (Intergovernmental Panel on Climate Change [IPCC] 2007 [Physical Science]).

Climate change on timescales of a few decades and longer is more strongly influenced by anthropogenic activities (IPCC 2013). Anthropogenic activities that contribute to climate change include changes in atmospheric composition due to anthropogenic emissions of carbon-containing greenhouse gases, aerosols, and ozone, as well as widespread changes in land cover associated with agriculture, deforestation, and urbanization. Due to the strong influence of anthropogenic activities on climate change, the United Nations Framework Convention on Climate Change (UNFCCC) and other organizations define the term *climate change* as solely related to human activity: "*a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods*" (United Nations 1992). Throughout this document, unless otherwise noted, the term *climate change* refers to changes in climate conditions on timescales of a few decades to a century resulting from anthropogenic activities.

It should be noted that in addition to anthropogenic activities, naturally occurring processes are also known to contribute to climate change. Volcanic eruptions, for example, spew dust and gases into the atmosphere that can affect global climate conditions. Dust from volcanic eruptions can have a large-scale cooling effect on the atmosphere by shading incoming solar radiation. This effect may be significant and can last from months to years, but does not contribute significantly to climate change on timescales of a few decades and longer (UCAR 2016). Changes in solar intensity and in earth's orbit around the sun also have the potential to affect climate conditions. However, changes in solar intensity have not significantly contributed to climate change over the past several decades (IPCC 2013), whereas changes in earth's orbit occurs on timescales of tens to hundreds of thousands of years and have negligible impact on timescales of a few decades to a century (IPCC 2013). Lastly, coupled interactions between slowly varying components of the earth system result in multi-decadal fluctuations in climate conditions. These naturally-occurring multi-decadal fluctuations are often considered to be low-frequency climate variability rather than climate change.

The concepts of *stationarity* and *non-stationarity* are closely related to the concepts of climate variability and climate change, respectively. With respect to climate, *stationarity* refers to a situation where weather and climate conditions vary over time, but the statistical characteristics of weather and climate—i.e., the average climate condition over time and the magnitude of climate variability—remain the same. By contrast, *non-stationarity* refers to a situation where weather and climate conditions vary over time, but the statistical characteristics do **not** remain the same. Non-stationarity occurs when there is a change in long-term average climate or in the range or character of climate variability, as occurs under climate change.

The concepts of *stationarity* and *non-stationarity* are directly related to the technical approach used in water resources, planning, and environmental analyses. For any given study, the study team must make assumptions regarding future weather and climate conditions. These assumptions directly affect subsequent analysis of future hydrology and environmental conditions, including water supplies, demands, and operations.

Weather conditions at any given place and time cannot be accurately predicted in more than a seven to ten days in advance (for example, see Epstein 1988 and Palmer 2000 for discussion of the fundamental limits of predictability in weather and climate). Over most of human history, however, the complex processes that govern weather systems have tended to average out with some consistency over a period of a few decades. Analysis of historical weather and climate conditions over long periods thus provided a reasonable estimate of future conditions, including long-term averages as well as the likely range of variability and extremes. Based on this multi-decadal stability, water resources, planning, and environmental analyses commonly characterized future climate conditions using the paradigm of *stationarity*, or the assumption that past climate conditions can be used to characterize expected future climate conditions (NOAA 2015). As a result, historical climate conditions were used as the basis for water resources and environmental planning, design, and management (McMahon 1993, Milly et al. 2008).

Climate change, however, has altered and will continue to alter weather and climate conditions on global, regional, and local scales. These changes affect the basic assumptions underlying water resources and environmental planning and decision making (IPCC 2014 [AR5 Impacts]). Most notably, the assumption of climate stationarity is no longer valid (for example, see Milly et al. 2008).

"For the longest period when calculation of regional trends is sufficiently complete (1901 to 2012), almost the entire globe has experienced surface warming."

IPCC 2013
(Physical Science Summary)

Under the paradigm of stationarity, using one historically observed climate scenario as the basis for characterizing future conditions is an accepted practice. By contrast, under the paradigm of non-stationarity—i.e., climate change—study teams must develop assumptions regarding future conditions that appropriately characterize projected climate conditions and that are relevant to the decisions that must be made in the study. In addition to understanding the physical, institutional, and regulatory factors that affect water resources management, effective planning ultimately depends on a firm understanding of climate change impacts on water supply, demand, and criteria that govern or guide water management. Planners, managers, and decision makers thus need reliable and relevant projections of future climate conditions to inform resource management decisions.

Throughout this document, the term *climate projection* refers to a simulation of future climate conditions under a given emissions scenario and corresponding concentrations of greenhouse gases and aerosols. As summarized in Section 2.2, global climate projections are generally developed using GCMs and regional climate projections are developed by downscaling GCM-based global projections over a region of interest. By contrast, the term *climate scenarios* refer to plausible and often simplified representations of future climate, based on an internally consistent set of climatological relationships that have been explicitly constructed for use in investigating the potential consequences of climate change. Climate projections often serve as the raw material for constructing climate scenarios; however, climate scenarios usually incorporate additional information, such as information from historical observations of weather and climate. Climate scenarios often serve as inputs to resource models, including hydrologic models and water resources operations models, for analysis of climate change risks and impacts and evaluation of climate change adaptation strategies. Methods for developing climate scenarios from climate projections are outlined in Section 5.2 of Reclamation 2014 (Technical Guidance), which provides guidance for incorporating climate change information into water resources planning studies.

2.2. Developing Future Climate Projections

Climate change is a direct result of changes in the earth's energy balance—e.g., the reflection or absorption of energy from the sun, re-radiation of energy from the earth surface to the atmosphere, and movement of energy within the earth system (Lindsey 2009). Large-scale atmospheric circulation and local winds, for example, are both driven largely by spatial differences in the absorption of energy by the atmosphere (Wallace and Hobbs 2006). As air in the atmosphere absorbs energy, it becomes warmer and begins to expand. As the air expands, its density decreases and it begins to rise. Differences in energy absorption and heating within the atmosphere result in density and pressure gradients that ultimately drive atmospheric circulation. Latent heating via evaporation from land and ocean surfaces and transpiration from plants, and the subsequent movement and precipitation of water vapor in the atmosphere, also play an important role in the earth's energy balance, as well as weather and climate conditions.

The amount of energy that is absorbed by the atmosphere depends on chemical composition of the atmosphere, in particular the concentrations of greenhouse gases and aerosols.

- Greenhouse gases absorb longwave radiation emitted by the earth, resulting in increased warming of the atmosphere. Major greenhouse gases including carbon dioxide (CO_2), methane (CH_4), ozone (O_3), nitrous oxide (N_2O), and water vapor (H_2O).

- Aerosols are minute solid or liquid particles suspended in the atmosphere. The effects of aerosols on the atmospheric energy balance depends on the composition and color of aerosol particles. Some aerosols such as sulfates and nitrates reflect incoming solar radiation, resulting in cooling of the atmosphere and the earth's surface. Others such as black carbon absorb solar radiation, which warms the atmosphere while shading the surface. Aerosols also affect the formation and characteristics of clouds, as well as chemical reactions in the atmosphere. The overall effect of human-caused aerosols on climate remains an area of active research.

Changes to the chemical composition of the atmosphere—including changes in greenhouse gases and aerosol concentrations—affect the atmosphere's energy balance. Changes in the atmosphere's energy balance subsequently affect atmospheric circulation, which in turn affects weather and climate. Atmospheric concentrations of greenhouse gases and aerosols play an increasingly important role in the earth's energy balance, and consequently in the global climate system (IPCC 2013).

Climate projections are typically developed by simulating changes in the earth's energy balance, and corresponding changes in weather and climate conditions, in response to specified changes in atmospheric composition. Development of climate projections thus generally involves three key components:

(1) Emissions scenarios

(2) Global climate models (GCM)

(3) Downscaling methods, including optional bias correction

Each of these components is briefly discussed below.

2.2.1. Emissions Scenarios

To analyze the impacts of human-caused greenhouse gas and aerosol emissions on climate, and to evaluate and plan for the potential impacts of climate change, the scientific community must first develop trajectories of future emissions and corresponding atmospheric concentrations.

> **"The goal of working with scenarios is not to predict the future, but to better understand uncertainties and alternative futures, in order to consider how robust different decisions or options may be under a wide range of possible futures."**
>
> **IPCC 2014**
> **(Scenario Process for AR5)**

Future emissions will depend on many factors, including regional and global demographics, technological and socioeconomic development, and potential efforts to reduce emissions. As a result, the future evolution of greenhouse gas and aerosol emissions is highly uncertain (IPCC 2000 [SRES

Summary]). Rather than attempting to predict the actual trajectory of future emissions—i.e., the quantity of emissions each month or year over the next century—the climate science community has developed a broad range of emissions scenarios that represent "*alternative images of how the future might unfold and are an appropriate tool with which to analyze how driving forces may influence future emissions outcomes and assess the associated uncertainties*" (IPCC 2000 [SRES Summary]). Developing and analyzing scenarios is a widely used approach to planning and decision-making in situations characterized by a high level of uncertainty. By considering a broad range of scenarios, planners and decision makers can address relevant "what if" questions and develop robust and effective strategies despite large uncertainty in future conditions.

Emissions scenarios represent "*estimates of future emissions based on our understanding of natural sources of greenhouse gases and on assumptions about . . . how much greenhouses gases will be released into the atmosphere by humans*" (AdaptNSW 2015). Each emissions scenario consists of a set of time-evolving values representing the emissions and corresponding atmospheric concentrations of various greenhouse gases and aerosol compounds that affect the earth's energy balance, as well as corresponding land use and land cover data. Emissions scenarios include both natural[5] and anthropogenic emissions. It should be noted that emissions scenarios are not scenarios of future climate, but instead are scenarios of the future trajectory of greenhouse gas and aerosol emissions and corresponding atmospheric concentrations. Projections of future climate conditions are then developed by using GCMs to simulate global climate under a specified emissions scenario.

IPCC initially developed emissions scenarios in 1990 (SA90 scenarios) and 1992 (IS92 scenarios) to facilitate coordinated analysis of climate change and its impacts by providing climate scientists around the world with a common foundation for modeling climate change. IPCC updated emissions scenarios in 2000 to incorporate improved data and understanding regarding the factors that drive greenhouse gas and aerosol emissions and underlying uncertainties. These scenarios were described in the IPCC Special Report on Emissions Scenarios (SRES) (IPCC 2000 [SRES Summary]) and are commonly referred to as the SRES scenarios. Climate projections under the SRES emissions scenarios served as the basis for the IPCC Third Assessment Report (TAR) (IPCC 2001) and Fourth Assessment Report (AR4) (IPCC 2007). IPCC updated emissions scenarios in 2009 to again incorporate improved data and understanding, to address new science questions that arose from the IPCC Third and Fourth Assessment Reports, and to provide scenario datasets consistent with updated

[5] Emissions scenarios account for some, but not all, natural sources and sinks of greenhouse gases and aerosols. In particular, volcanic emissions are not considered in future emissions scenarios due to the inability to reasonably predict future volcanic activity. The extent to which climate-carbon cycle feedbacks are represented varies between emissions scenario; climate-carbon cycle feedbacks occur when climate conditions affect natural sources and sinks of carbon-based greenhouse gases.

climate models (Moss et al. 2010). Climate projections under the RCP scenarios served as the basis of the IPCC Fifth Assessment Report (AR5) (IPCC 2014 [AR5 Synthesis]).

SRES and RCP emissions scenarios are discussed in more detail in Section 3.1.2.

2.2.2. Global Climate Models

Global climate models (GCM) are computer models designed to help understand and simulate global and regional climate, including the climatic response to changing concentrations of greenhouse gas emissions.

The National Oceanographic and Atmospheric Administration's (NOAA) National Weather Service (NWS) defines climate models as "*mathematical model[s] for quantitatively describing, simulating, and analyzing the interactions between the atmosphere and underlying surface (e.g., ocean, land, and ice)*" (NWS 2015). NOAA's Climate Prediction Center (CPC) further describes GCMs as computer models capable of reproducing the earth's weather patterns and that can be used to predict and analyze changes in global weather and climate (NWS CPC 2015).

Figure 2 shows a conceptual schematic illustration of a GCM. GCMs represent the key physical processes that affect weather and climate, including the movement of energy, mass, and moisture within the atmosphere and between the atmosphere and the underlying surface. GCMs represent the atmosphere, oceans, land, and ice on a three-dimensional grid and simulate the movement of mass and energy vertically and horizontally between grid cells, along with the resulting weather conditions—e.g., temperature and precipitation—at each grid cell.

Numerous GCMs have been developed by modeling centers around the world, including universities, government agencies, and national laboratories and research centers. A total of 23 GCMs from 16 modeling centers contributed to the Coupled Model Intercomparison Project Phase 3 (CMIP3) Multi-Model Dataset which supported the IPCC TAR and AR4, while a total of 61 models from 27 modeling centers contributed to the CMIP Phase 5 (CMIP5) Multi-Model Dataset which supported the IPCC AR5.

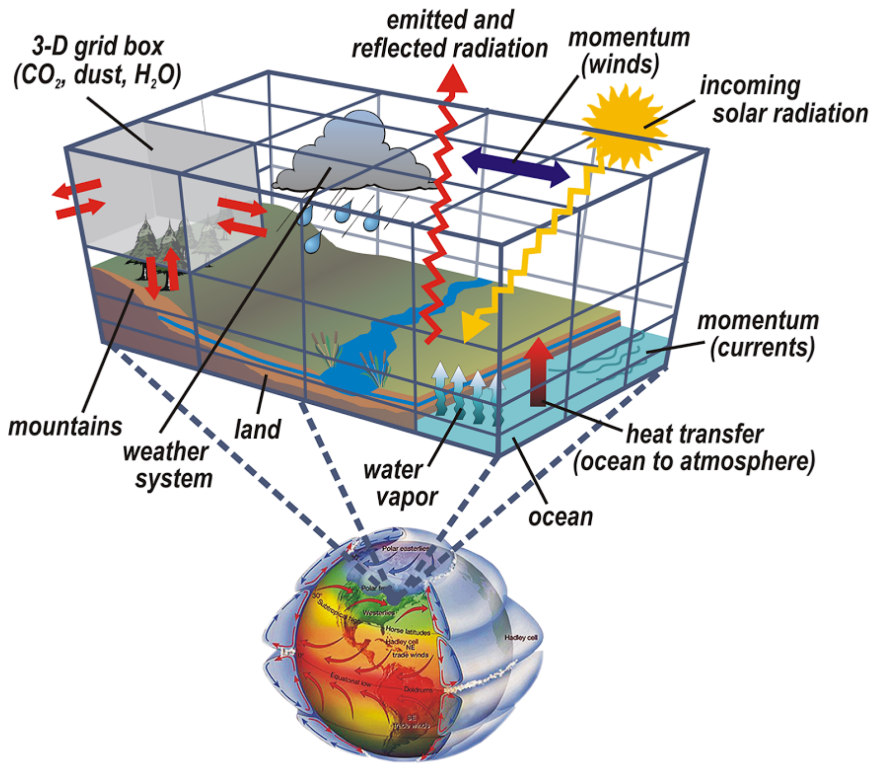

Figure 2: Schematic illustration of a global climate model (GCM).

While different GCMs often share common methods and assumptions—including parameterizations,[6] modules, and in some cases sub-models—each model represents a unique (though not necessarily independent) representation of the global climate system (Sanderson et al. 2015). As a result, different GCMs exhibit different levels of skill in simulating different aspects of observed 20th century climate conditions. For example, a GCM may exhibit high skill in simulating northern hemisphere precipitation patterns compared to other models while simultaneously exhibiting low skill in simulating southern hemisphere precipitation patterns. Similarly, the projected climate change in response to a given emissions scenario differs between GCMs. Differences between GCMs are often difficult to diagnose due to the large number of physical processes and complex process interactions represented by each GCM (Sanderson et al. 2015).

[6] Parameterization in a weather or climate model refers to using simplified equations and relationships to represent processes that occur at too small a scale, are too complex, or about which too little is known to simulate explicitly. For example, processes such as cloud formation, precipitation, and turbulence occur at spatial scales much smaller than the model grid resolution. It is not possible to simulate these processes explicitly due to limitations of existing computer resources and physical understanding. However, these processes are fundamental to the atmosphere and cannot be neglected. Instead, simplified equations and relationships referred to as *parameterizations* are used to represent these processes.

2.2.3. Downscaling and Bias Correction

The spatial resolution of most GCM-based climate projections is typically on the order of one to two degree latitude by one to two degree longitude, or roughly 110-220 kilometers (km) by 110-220 km over mid-latitudes. Local weather and climate conditions, by contrast, exhibit substantial variability across a degree of latitude or longitude due to variations in topography, land cover, and many other factors that affect local climate. As a result, the spatial resolution of GCMs is too coarse to use in most regional or basin-scale analyses. Applying GCM-based climate projections to support regional and basin-scale planning and decision making therefore requires a method to downscale coarse-resolution GCM results to finer spatial resolutions (Wood et al. 2004, Fowler et al. 2007, and IPCC 2013).

Numerous methods have been developed to downscale coarse-resolution GCM projections to finer spatial resolutions over a selected area to support regional and basin-scale analyses, planning, and decision making. Downscaling methods fall into two broad categories: dynamical methods and statistical (non-dynamical) methods. Dynamical downscaling methods use finer-resolution regional climate models (RCM) to simulate the three-dimensional and multivariate atmospheric response to global climate change, nesting the RCM inside the GCM over a selected region. The RCM then simulates weather and climate conditions over the selected region at a finer resolution that is more applicable to a regional and local planning and decision making. Statistical (non-dynamical) downscaling methods rely on relationships between observed (historical) large-scale and finer-scale weather and climate conditions. These relationships are applied to the large-scale GCM results to develop GCM-based projections at the finer spatial scale.

Dynamical and statistical downscaling methods each exhibit a number of benefits and limitations (Wood et al. 2004 and Fowler et al. 2007). For example, dynamical downscaling uses RCMs that represent the physical processes which govern regional weather and climate conditions and thereby account for physical processes and interactions that affect local weather and climate, such as snow-albedo and cloud feedbacks. However, dynamical downscaling is extremely computationally expensive, limiting the number of projections that can be practically downscaled. In addition, dynamical downscaling methods often do not address biases inherent in GCMs, and these methods may also be affected by biases in the RCMs used to downscale GCM results.

By contrast, statistical downscaling is computationally efficient, incorporates observed weather and climate information, and often includes a bias correction step to remove biases in GCM results (see discussion below). However, statistical downscaling methods require accurate observational data at fine spatial resolutions and over a long period of record, which may not be available over all regions. Many statistically downscaled datasets are based on gridded meteorology datasets developed by interpolating meteorological station data; these datasets may exhibit notable biases in some areas due to the limited number of stations and extensive interpolation between stations (Maurer et al. 2002, Livneh et al. 2013, and Abatzoglou 2011). In addition to data quality issues, statistical downscaling methods inherently assume that observed relationships between large-scale and finer-scale weather and climate conditions will remain valid under changing climate conditions—in other words, statistical downscaling methods assume that relationships between large-scale and finer-scale weather and climate conditions are stationary. It is generally acknowledged that these relationships will in fact change under changing climate conditions; however, the magnitude of errors introduced by the stationarity assumption is not well understood at this time.

In addition to downscaling, GCM projections are often adjusted to remove or reduce biases in model-simulated weather and climate conditions. While modern GCMs accurately represent many important characteristics of weather and climate, no model is a perfect representation of the real world—in other words, all models exhibit biases. In this context, the term *bias* refers to differences between simulated and observed climate conditions—e.g., differences between simulated and observed mean annual temperature or precipitation over a region of interest. The term *bias correction* thus refers to the use of a statistical procedure to adjust GCM projections to remove differences between simulated and observed climate conditions. The primary causes of bias in GCM simulations include (IPCC 2007 [Physical Science]):

- The coarse resolution of GCMs and the corresponding inability to resolve important stationary features such as land surface topography and land-water interfaces along coastlines

- The use of simplified parameterizations to represent physical processes that occur at too small a scale or are too complex to be represented physically (see Section 2.2.2.)

Numerous studies have evaluated biases in individual GCMs or across multi-model ensembles of GCM simulations. While it is quite easy to identify biases, it is often difficult to determine the root cause of a particular model bias (Palmer and Weisheimer 2011). Model biases can significantly affect impact studies that use climate projections to evaluate hydrologic and ecosystem response to climate change. As a result, bias correction is often required before GCM outputs can be used as inputs to other types of models. Numerous approaches have been developed to remove biases from climate model outputs; further discussion of bias correction methods is beyond the scope of this document.

2.3. Incorporating Climate Projections into Water Resources and Environmental Analyses

Effective management of water and environmental resources often requires understanding current and future water supplies and demands, and the ability of current and/or proposed infrastructure and operations to meet those demands now and into the future. Reclamation study teams therefore need practical, relevant, and credible information regarding projected future climate to support analyses of future hydrology and environmental conditions, and to inform decision-makers, stakeholders, and the public.

As required under several executive and secretarial orders, departmental policies, and bureau directives and standards, Reclamation must consider the potential effects of climate change in planning and decision making, including design and analysis of current and proposed infrastructure and operating plans (see Section 1.1).

Reclamation recently issued guidance for incorporating climate projection information into water resources and environmental analyses and planning studies (Reclamation 2014 [Technical Guidance]). For any given study, the guidance assists study teams in determining an appropriate level of climate change analysis, ranging from no analysis of climate change to a quantitative analysis of climate change effects. If a quantitative analysis is selected, the guidance assists study teams in identifying a specific climate change method to use in the analysis. However, the guidance does not address selecting a climate projection dataset or selecting a subset of projections for use in a detailed analysis. (Available climate projection datasets are described in Section 4 of this document; methods for selecting a subset of climate projections for use in a detailed analysis are described in Sections 5.)

Numerous methods have been developed to incorporate climate change information into analyses to support water resources and environmental planning and decision making. Generally, climate projection information is incorporated into a given analysis through the inputs to resource models used in the analysis, including:

- Hydrologic models, water demands models, and water resources planning and operations models used to simulate and analyze water supplies, demands, and management

- Resource models used to simulate and analyze environmental and habitat conditions and ecosystem behavior

- Economic models used to simulate and analyze economic cost and benefits

In some cases, downscaled climate projections are used directly as inputs to the study models. In other cases, climate projection information is incorporated by modifying model inputs that are based on historical observations to represent the projected change in certain aspects of climate. In the latter case, climate projection information is merged with historical data to characterize future climate conditions. For example, precipitation and temperature inputs to a hydrologic model based on historical observations may be modified to reflect projected changes in monthly precipitation and temperature while preserving the sequencing and relative magnitude of climate variability from the historical record. This type of method allows technical specialists on a given study team to incorporate aspects of climate change that are represented well by GCMs such as long-term trends, while relying on historical information for aspects of weather systems and natural climate variability that are not represented sufficiently well such as daily precipitation frequency and intensity (Reclamation 2014 [Technical Guidance]).

Incorporating climate projection information into water resources and environmental analyses typically involves several interrelated steps, including but not limited to:

(1) Selecting hydrologic, demands, planning and operations, and/or other resource models to be used in the study

(2) Identifying model inputs that must be adjusted to reflect projected climate change

(3) Selecting climate projection dataset

(4) Selecting individual climate projections to be considered in analysis

(5) Developing climate scenarios for use in a detailed analysis

(6) Developing model inputs for each climate scenario

A wide range of modeling approaches have been developed to simulate water resources and environmental systems, ranging from simple statistical models based on linear relationships between variables to highly detailed physically-based and rule-based models that explicitly simulate physical processes, process interactions, and operational decisions. Study teams should select modeling approaches that are consistent with the needs of their particular study, including the questions to be address and the level of detail required (Reclamation 2014 [Technical Guidance]).

Once a model has been selected, climate projections are incorporated by developing model input datasets that reflect projected future climate conditions. Any given modeling approach requires a number of inputs, including time-varying inputs (e.g., precipitation and temperature inputs to a hydrologic model) as well as constant inputs (e.g., model coefficients in a statistical model). The type(s) of climate projection information required for a given study depend on the selected modeling approach, the associated inputs, and the study questions to be addressed. Climate-related inputs for typical hydrologic and water resources models include precipitation and temperature, and may include other relevant variables such as humidity, wind speed, solar (shortwave) radiation, and atmospheric carbon dioxide concentration.

For any given study, the technical specialists on the study team must select a specific set (or sets) of GCM or downscaled climate projections for their analysis. Several widely used climate projection datasets are summarized in Section 4, including multi-model GCM datasets and multi-model datasets of downscaled GCM projections. When selecting a projection dataset for a given study, study teams should consider the study objectives to determine the relevant spatial and temporal scales and specific climate variables and aspects of climate variability. Many climate projection datasets provide a large number of individual climate projections from many different GCMs and emissions scenarios. In addition, climate projection datasets may include multiple projections for a single combination of GCM and emissions scenario, each differing only in its initial state at the start of the projection (see Section 3.4.3). As a result, detailed analysis of all available climate projections from a selected dataset is often not feasible given the practical limitations of study budget and schedule. Study teams must select a subset of climate projections from the selected dataset to be included in further analysis. A variety of methods are available to select a subset of climate projections from a given dataset; several widely used methods are summarized in Section 5.

After selecting a set of climate projections to be considered in a given study, the technical specialists on the study team must then develop climate scenarios for use in a detailed analysis. As summarized in Section 2.1., *climate projections* are simulations of future climate conditions under a given emissions scenario and corresponding concentrations of greenhouse gases and aerosols. By contrast, *climate scenarios* are plausible and often simplified representations of future climate constructed to use in investigating the potential consequences of climate change. Climate scenarios often serve as inputs to resource models, including hydrologic models and water resources operations models, for analysis of climate change risks and impacts and evaluation of climate change adaptation strategies. Methods for developing climate scenarios from climate projections are outlined in Reclamation 2014 (Technical Guidance) in Section 5.2., which provides guidance for incorporating climate change information into water resources planning studies.

3. Considerations for Selecting Climate Projection Information

The climate and hydrology technical specialists on a given study team must make a number of choices when selecting the climate projection information basis for a specific study. Should we use projections from CMIP3 or CMIP5? Should we use GCM projections directly or should we use downscaled projections? How should we select an appropriate number of projections for use in a detailed analysis?

The purpose of this section is to identify important choices that these technical specialists must make to choose appropriate climate change information for a given study and to discusses key considerations in making each of these choices. This section is intended to help *technical specialists* recognize key decisions that are often made on an *ad hoc* basis. In addition, this section is intended to help *other study team members* understand the decisions and considerations required to choose appropriate climate change information in order to facilitate documentation and interpretation study data, methods, and results. This section does not, however, provide direct guidance to study teams regarding selection of climate projection information.

3.1. Choosing between CMIP3 and CMIP5

The climate science community has not determined that CMIP5 is a better or more reliable source of climate projection information than CMIP3. The World Climate Research Program (WCRP) therefore suggests that the CMIP5 Multi-Model Dataset should be considered an addition to, and not a replacement of, the CMIP3 Multi-Model Dataset.

The CMIP3 and CMIP5 multi-model datasets were both developed to support broad analysis of climate change and its impacts to society and the environment. The overall approach to developing global projections of 21st century climate is virtually identical for CMIP3 and CMIP5. As summarized in Section 2.2, both datasets were developed by using GCMs to simulate future climate conditions under emissions scenarios representing possible future trajectories of greenhouse gas and aerosol emissions. Both datasets provide output from these global simulations, including projections of future precipitation, temperature, and other important weather and climate variables. However, several important details differ between the two datasets, including the features and capabilities of the models used in each dataset, the emissions scenarios considered, and the temporal resolution and model output variables included in each dataset.

This section briefly summarizes key differences between the CMIP3 and CMIP5 multi-model datasets. Differences between the models used in CMIP3 and CMIP5 are discussed in Section 3.1.1 and differences between the emissions scenarios used in each dataset are discussed in Section 3.1.2. Differences between the model outputs available for each dataset are briefly summarized in Section 3.1.3.

3.1.1. Differences between Global Climate Models

Climate models are the primary tools used to evaluate the climate system response to changes in atmospheric composition, including changes resulting from natural and anthropogenic greenhouse gas and aerosol emissions (IPCC 2013). While the models used in CMIP3 and CMIP5 are fundamentally similar, many of the models used in CMIP5 incorporate a number of improvements compared to those used in CMIP3.

Improvements in models used in CMIP5 generally reflect advances in parameterization of physical processes, representation of new physical processes, and increases in model resolution (IPCC 2013). Improvements in atmospheric parameterizations, for example, include advances in representation of cloud processes (aerosol-cloud and cloud-radiation feedbacks), atmospheric convection, and atmospheric boundary layer processes (IPCC 2013). Important improvements in land surface parameterization include representation of vegetation dynamics, land-atmosphere carbon exchanges, and sub-gridscale hydrology in some models (IPCC 2013).

In addition to improvements to traditional global climate models (GCM), CMIP5 reflects the emergence of earth system models (ESM). GCMs have long been the ‘standard’ tool for understanding the dynamics of the climate system and for making projections of future climate changes in response to changes in greenhouse gas and aerosol concentrations in the atmosphere. ESMs expand on GCMs to include dynamic representation of the carbon cycle, including biogeochemical processes that affect the exchange of carbon dioxide between the land, oceans, and atmosphere (IPCC 2013).

Figure 3 shows a schematic illustration of the difference between GCMs and ESMs. Like GCMs, ESMs are complex mathematical models that represent the key physical processes that affect weather and climate, including the movement of water and energy within the atmosphere and between the atmosphere and the underlying land and ocean surfaces. Similarly, like GCMs, ESMs represent the atmosphere, oceans, land, and ice on a three-dimensional grid; simulate the movement of water and energy vertically and horizontally between grid cells; and simulate the resulting weather and climate conditions—e.g., temperature and precipitation—at each grid cell. Unlike GCMs, however, ESMs include an interactive carbon cycle model that allows for dynamic simulation of carbon sources and sinks and their interactions with the global climate system. Some ESMs also include dynamic representation of biogeochemical processes affecting nitrogen and sulfur in the atmosphere. The objective of ESMs is to simulate changes in land and ocean interaction with atmospheric carbon dioxide and aerosols, along with subsequent feedbacks on global climate.

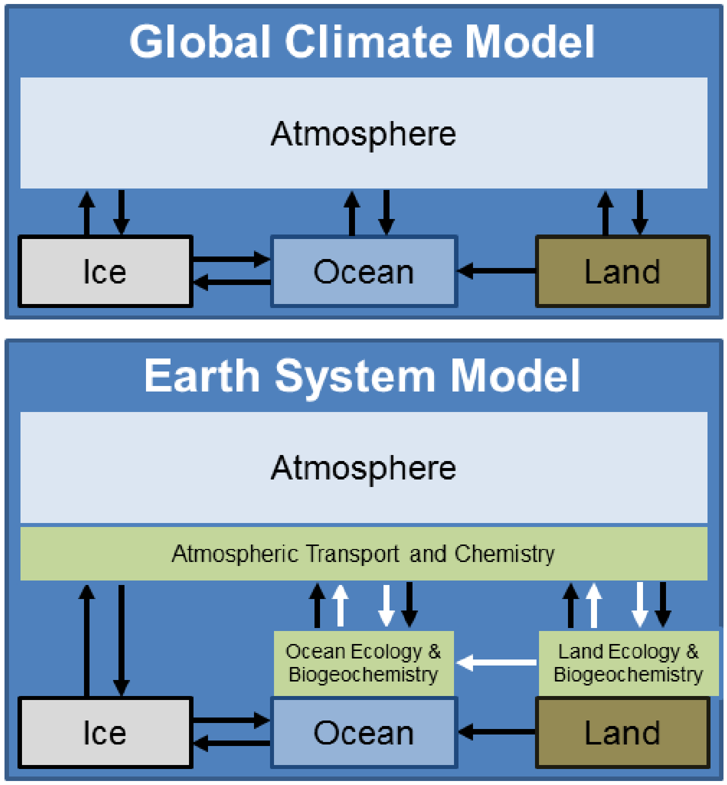

Figure 3: Schematic illustration of the difference between GCMs and ESMs. Black arrows represent exchanges of water and energy between components; white arrows represent exchanges of carbon between components.

As summarized by IPCC (2013), more than half of the models used in CMIP5 include dynamic representation carbon uptake and release from land and/or oceans, while more than one in four models includes dynamic representation atmospheric chemistry and their interactions with climate. By contrast, none of the models used in CMIP3 included dynamic representation of land and ocean carbon fluxes, and only one included dynamic representation of atmospheric chemistry. In addition, nearly all models that contributed to CMIP5 include some degree of interactive aerosols, compared to just a few of the models used in CMIP3. However, representation of biogeochemical processes varies widely among models used in CMIP5.

Despite these improvements, however, IPCC notes that for most evaluation metrics, "the CMIP3 and CMIP5 model performances are broadly similar" (IPCC 2013). Similarly, projected changes in future climate are generally similar for the models used in CMIP3 and CMIP5 (see Section 3.1.5). Differences between the models used in CMIP5 compared to those used in CMIP3 are, therefore, not sufficient to suggest that CMIP3 models are outdated or obsolete, but rather that both the CMIP3 and CMIP5 are appropriate for use in evaluating projected future climate conditions.

3.1.2. Differences between Emissions Scenarios

As summarized in Section 2.2., to analyze the impacts of anthropogenic greenhouse gas and aerosol emissions on climate and to plan for the potential impacts of climate change, the scientific community must first develop trajectories of future emissions and corresponding atmospheric concentrations. Rather than attempting to predict the trajectory of future emissions, which depend on a multitude of highly uncertain factors, the climate science community has developed a suite of emissions scenarios that represent "*alternative images of how the future might unfold and are an appropriate tool with which to analyze how driving forces may influence future emissions outcomes and assess the associated uncertainties*" (IPCC 2000 [SRES Summary]). Each emissions scenario consists of a set of time-evolving values representing the emissions and/or atmospheric concentrations of various greenhouse gases and aerosol compounds that affect the earth's energy balance, as well as corresponding land use and land cover data.

Scenarios are widely used by planners and decision makers in situations characterized by a high level of uncertainty. By considering a broad range of scenarios or storylines that address relevant "what if" questions, planners and decision makers can develop robust and effective strategies despite large uncertainty in future conditions. Emissions scenarios represent "*estimates of future emissions based on our understanding of natural sources of greenhouse gases and on assumptions about . . . how much greenhouses gases will be released into the atmosphere by humans*" (AdaptNSW 2015). As noted in Section 2.2.1., emissions scenarios are not scenarios of future climate, but instead scenarios of the future trajectory of greenhouse gas and aerosol emissions and corresponding atmospheric concentrations; projections of future climate conditions are then developed by using GCMs to simulate future climate under a specified emissions scenario.

The emissions scenarios used in CMIP5 differ from those used in CMIP3. In CMIP3, projections of future climate change are based on emissions scenarios described by the IPCC Special Report on Emissions Scenarios (IPCC 2000 [SRES]), referred to as the SRES emissions scenarios. The SRES emissions scenarios were developed by using integrated assessment models (IAM) [7] to simulate specific socioeconomic scenarios representing different "*storylines about future demographic and economic development, regionalization, energy*

[7] Integrated Assessment Models (IAM) are computer models that represent the scientific and socioeconomic factors that affect climate change. IAMs combine physical and social science models of demographics, policy, and economics to evaluate how assumptions regarding future socioeconomic and policy drivers will affect anthropogenic emissions and global climate. Additional discussion of IAMs is provided by Janetos et al. 2009.

production and use, technology, agriculture, forestry, and land use" (IPCC 2013) Each of the SRES scenarios thus represents a specific socioeconomic scenario and resulting greenhouse gas emissions and concentrations.

In CMIP5, by contrast, projections are based on a new set of emissions scenarios described by Moss et al. (2010) and van Vuuren et al. (2011), referred to as "representative concentration pathways" (RCP). In contrast to the SRES scenarios, the RCP scenarios were developed through a new parallel process for scenario development. Like the SRES emissions scenarios, the RCPs consist of trajectories of greenhouse gas emissions and concentrations. However, for the RCPs, emissions and concentration trajectories were developed independently of specific socioeconomic storylines or scenarios. This approach recognizes that a given trajectory of emissions and concentrations could occur under multiple socioeconomic scenarios. RCPs were thus developed independently of socioeconomic scenarios to allow parallel development of climate projections and socioeconomic storylines, as well as to facilitate interaction between the science communities focusing on the physical science aspects of climate change and those focusing on the socioeconomic and policy aspects (IPCC 2013).

Future trajectories of anthropogenic radiative forcing—i.e., the effects of anthropogenic greenhouse gas emission on the atmospheric energy balance, expressed as Watts per meter squared (W/m^2)—under the SRES and RCP emission scenarios are illustrated in Figure 4, along with the projected change in global average surface temperature. The range of projected change in temperature over the 21st century is generally similar between the SRES and RCP scenarios, with the projected change under RCP 4.5 similar to under SRES scenario B2 and projected change under RCP 8.5 slightly greater than under SRES scenario A2. Radiative forcing under RCP 8.5 closely follows that under SRES scenario A2, while RCP 4.5 closely follows SRES scenario B1. Radiative forcing under RCP 2.6 is lower than all SRES scenarios, whereas RCP 6.0 is slightly lower than SRES scenario B1 through 2060, then increases above B1 through the end of the 21st century.

Note that IPCC (2000) [Special Report on Emissions Scenarios] discusses a total of six emissions scenarios. All six scenarios are shown in Figure 4; however, scenarios A1FI, A1B, and B2 are not included in the CMIP3 multi-model dataset.

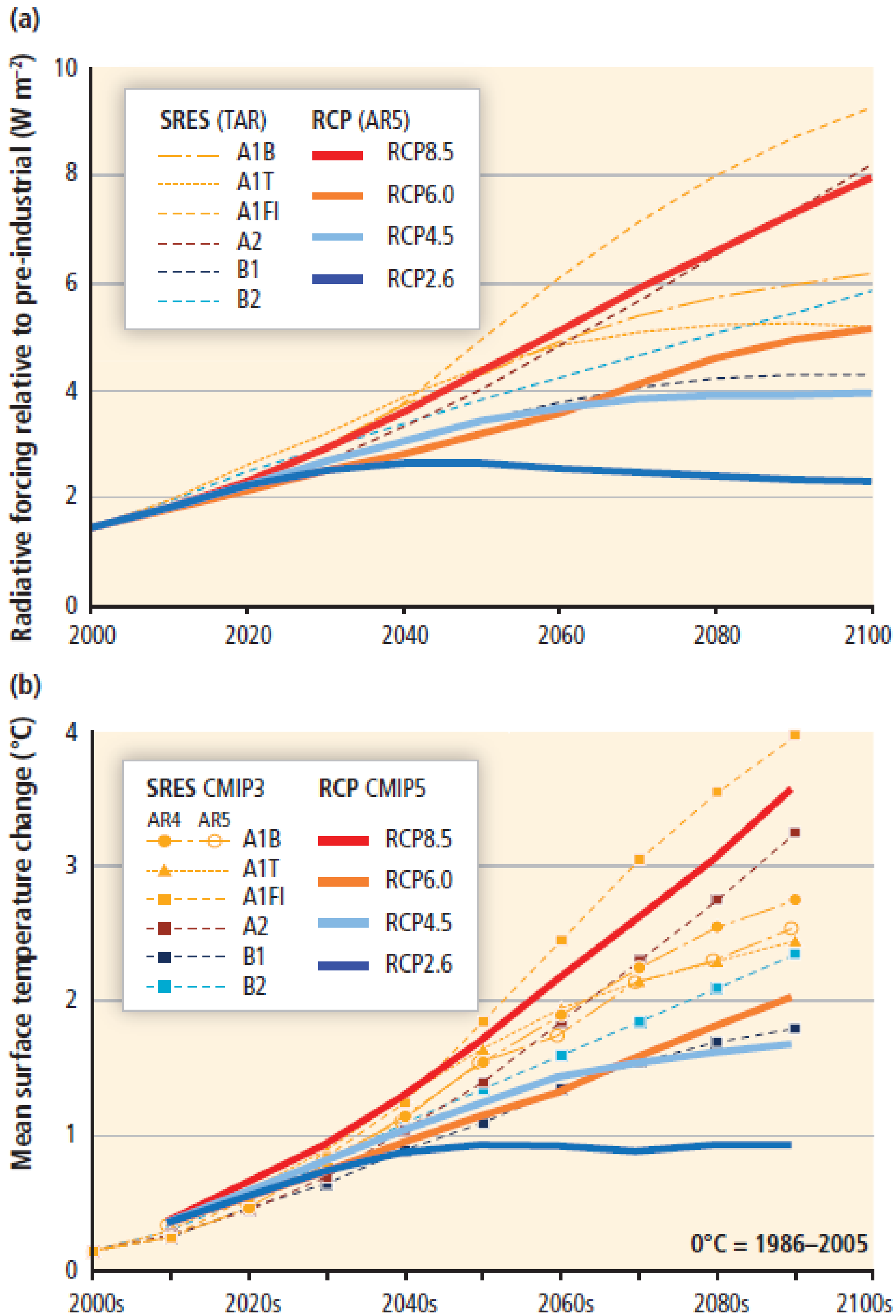

Figure 4: (a) Projected radiative forcing [W/m^2] and (b) projected change in global average surface temperature degrees Celsius (°C) over the 21st century under the SRES emissions scenarios used in CMIP3 and the RCPs used in CMIP5. Temperature changes are decadal averages based on the multi-model ensemble mean. Source: AdaptNSW (2015, used by permission, all rights reserved).

Given the tremendous uncertainty in future emissions, there is little basis in most cases for selecting climate projections based on an emissions scenario: each emissions scenario represents a plausible trajectory of future emissions and corresponding changes in atmospheric composition, and all scenarios are generally considered equally likely. Historical emissions since the year 2000 have been consistent with the higher emission SRES and RCP scenarios (SRES scenario A2 and RCP 8.5, respectively), rather than the moderate and lower emissions scenarios. However, it is important to note that projected climate conditions are generally similar under all emissions scenarios through the 2040s. Projected climate conditions under different emissions scenarios do not diverge significantly until the latter half of the 21st century. The choice of emissions scenario is therefore less likely to affect study results if the study period is limited to the first half of the 21st century, but this choice is very likely to affect results if the study period extends into the latter half of the century.

Lastly, it should be emphasized that the RCP scenarios used in CMIP5 are neither improved nor more accurate representations of future emissions than the SRES scenarios used in CMIP3. Both the SRES and RCP emissions scenarios represent valid scenarios of future anthropogenic greenhouse gas emissions to support analysis of climate change and its impacts on water and environmental resources.

3.1.3. Differences between Availability of Model Outputs

The temporal coverage and temporal resolution of model outputs available from the CMIP3 and CMIP5 multi-model datasets vary widely between models and scenarios. Similarly, the availability of model outputs differs between model output variables, with some models providing outputs for many more variables than others. In both the CMIP3 and CMIP5 datasets, monthly model outputs of primary climate variables—e.g., monthly mean temperature and monthly accumulated precipitation—are available from virtually all models for the primary scenarios, including pre-industrial and 20th century climate scenarios from both datasets, SRES scenarios B1, A1B, and A2 from the CMIP3 dataset, and RCPs 4.5 and 8.5 from the CMIP5 dataset. Daily model outputs are available for many of the CMIP3 models for selected scenarios and time periods, but generally not for the complete 20th and 21st centuries. By contrast, daily model outputs are available for a larger portion of the CMIP5 models and scenarios. In addition, while model outputs differ between models, the CMIP5 dataset generally includes a larger number of model output variables compared to the CMIP3 dataset.

In cases where study objectives require data at higher temporal resolution—e.g., daily rather than monthly—or for additional climate variables, study teams may need to consider data availability as a factor in selecting between the CMIP3 and CMIP5 multi-model datasets.

3.1.4. Comparison of Model Results: 20th Century Simulations

Several studies have compared various spatial and temporal characteristics of simulated precipitation, temperature, and other important variables between the CMIP3 and CMIP5 multi-model datasets. Detailed summaries of comparisons between CMIP3 and CMIP5 models are provided by IPCC 2013 and NOAA 2014. Overall, studies suggest that models in the CMIP5 multi-model dataset demonstrate general improvements in simulating several aspects of observed 20th century climate compared to the CMIP3 models, including improvements in large-scale patterns and magnitudes of average annual precipitation and temperature, regional-scale average annual temperature, globally-averaged temperature trends, and precipitation extremes (IPCC 2013). For example, improvements in model capabilities in simulating global annual average temperature and precipitation patterns between CMIP2[8], CMIP3, and CMIP5 are illustrated in Figure 5 (IPCC 2013).

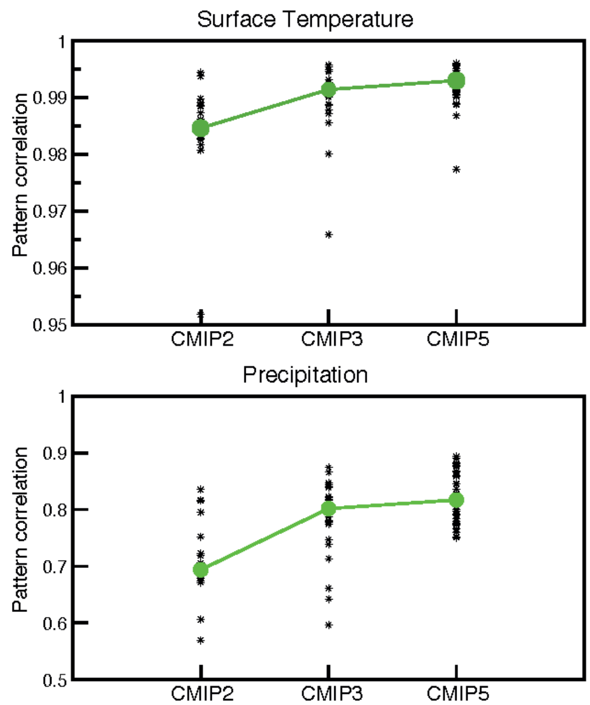

Figure 5: Spatial pattern correlation between observed and simulated annual mean temperature (top) and precipitation (bottom) over the globe. Larger values indicate better agreement between simulated and observed spatial patterns; black symbols represent individual models and green symbols indicate the median value over all models. Source: FAQ 9.1, Figure 1 from Flato et al. 2013 in IPCC. Used by permission.

[8] Coupled Model Intercomparison Project Phase 2 (CMIP2) was completed between 1996 and 1997. An overview of CMIP2 and summary of key results are provided by Covey et al. 2003.

The CMIP5 models also show modest improvements in simulating low-frequency modes of climate variability, including the El Niño-Southern Oscillation (ENSO), Pacific Decadal Variability, and Atlantic Multidecadal Variability (NOAA 2014). IPCC 2013 also notes that there are no categories for which CMIP5 models perform worse overall than their predecessor models in CMIP3. However, it should be emphasized that model performance varies substantially between models: "*No model scores high or low in all performance metrics, but some models perform substantially better than others for specific climate variables or phenomena*" (IPCC 2013).

Despite modest improvements in individual model performance compared to observed 20th century climate, performance of the multi-model ensemble mean did not show significant improvement between CMIP3 and CMIP5. Moreover, CMIP5 models continue to exhibit many of the biases exhibited by CMIP3, particularly with respect to simulated precipitation characteristics (IPCC 2013, NOAA 2014, Liu et al. 2014, Wuebbles et al. 2014, and Sun et al. 2015). As a result, the climate science community has not determined that CMIP5 is a better or more reliable source of climate projection information than CMIP3. The WCRP therefore suggests that the CMIP5 Multi-Model Dataset should be considered an addition to, and not a replacement of, the CMIP3 Multi-Model Dataset unless and until the climate science community determines otherwise (Reclamation et al. 2013).

3.1.5. Comparison of Model Results: 21st Century Projections

Several studies have attempted to compare projections of 21st century climate between the CMIP3 and CMIP5 multi-model datasets. However, the lack of common emissions scenarios between CMIP3 and CMIP5 make it difficult to directly compare 20th and 21st century simulations between the two datasets (Knutti and Sedláček 2012, IPCC 2013, and NOAA 2014). Direct comparison between CMIP3 and CMIP5 climate projections is further complicated by the inclusion of different models (see Section 3.1.1.) and different numbers of individual projections available for a given model.

At the global scale, recent studies indicate a general consistency in simulated large-scale climate patterns and projected climate change over the 21st century between the two datasets (IPCC 2013). In particular, Knutti and Sedláček (2012) found that despite differences between the models and emissions scenarios used in CMIP3 and CMIP5, the magnitudes and spatial patterns of projected changes in annual average temperature and precipitation are "*remarkably similar in CMIP3 and CMIP5, indicating that the large-scale features of climate change are robust.*" For example, Figure 6 shows the projected change in 21st century global-average surface temperature from CMIP3 under the SRES emissions scenarios (left panel) and from CMIP5 under the RCP scenarios (right panel), along with estimates of what the CMIP3 models would have projected had they been used to simulate the RCP scenarios (box plots).

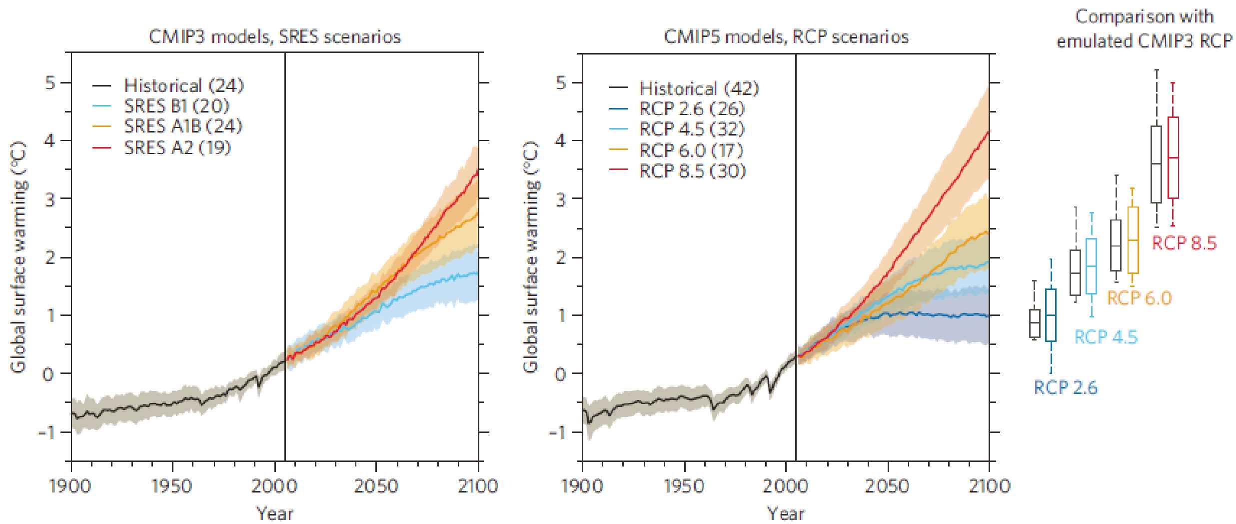

Figure 6: Projected changes in global-average surface temperature from CMIP3 models under the SRES emissions scenarios (left panel) and CMIP5 models under the RCP scenarios (right panel), and the range of projected changes in surface air temperature by the end of the 21st century from CMIP5 models and from estimates of CMIP3 response to RCP scenarios. Source: Figure 1 from Knutti and Sedláček (2012). Used by permission, all rights reserved.

Estimates of how the CMIP3 models would have responded under the RCP scenarios were developed using a simplified climate model referred to as the Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC). MAGICC was calibrated to reproduce results from 19 of the CMIP3 GCMs, and then used to estimate projected changes in temperature that each GCM would project under the RCP scenarios. These and other studies demonstrate that despite substantial differences between the models used in CMIP3 and CMIP5 (see Section 5.1.1.) and the emissions scenarios used in CMIP3 and CMIP5 (see Section 5.1.2.), the magnitude and spread of projected climate change is generally consistent between the datasets at continental and larger scales (IPCC 2013).

While several studies have illustrated the overall similarity between CMIP3 and CMIP5 projections at larger scales, recent studies demonstrate notable differences in projections of regional-scale climate changes between the two datasets. Differences in projections of regional-scale climate between CMIP3 and CMIP5 depend on the region, time period, and climate variable of interest. Few studies have conducted detailed analysis of differences in regional-scale climate change based directly on global model outputs available in the CMIP3 and CMIP5 multi-model datasets. Using statistically downscaled projections[9] from both datasets, Reclamation et al. (2013) found that:

> *"A comparison of downscaled CMIP5 and CMIP3 climate projections over the [Western United States] shows broad regional similarities (e.g., similar levels of warming throughout much of the West and similar precipitation trends towards the North and Southwest). There are also notable differences in some regions (e.g., greater warming over the Upper Columbia Basin, less precipitation over the northern Great Plains, and more precipitation over California and the Upper Colorado Basin from CMIP5 compared to CMIP3). Projections showing wetter portions of California and the Upper Colorado Basin are notable because they challenge previous projections from CMIP3 that suggested these regions will become drier, resulting in reduced runoff. It is important to recognize that, while CMIP5 offers new information, more work is required to better understand CMIP5 and its differences from CMIP3."*

It should be noted that the choice of downscaling method may affect differences in projected climate change between the CMIP3 and CMIP5 multi-model datasets. Further analysis is needed to understand the extent and causes of differences in projected regional-scale climate change between the CMIP3 and CMIP5 multi-model datasets.

As noted in Section 3.1.1., the climate science community has not determined that CMIP5 is a better or more reliable source of climate projection information than CMIP3. The WCRP therefore suggests that the CMIP5 Multi-Model Dataset should be considered an addition to, and not a replacement of, the CMIP3 Multi-Model Dataset unless and until the climate science community determines otherwise.

3.1.6. Additional Consideration Regarding Ongoing Studies and Consistency with Previous Studies

Additional considerations in choosing between CMIP3 and CMIP5 may apply when a given study builds upon previous analyses of climate change. Consider, for example, the following two situations:

- **Ongoing Studies:** A study was initiated using climate projection information from CMIP3, and the CMIP5 Multi-Model Dataset subsequently became available during the course of the study. Should the study team revise their analysis to use climate projection information from CMIP5, either by replacing the projections from CMIP3 with projections

[9] It should be noted that statistical downscaling may affect projected changes.

from CMIP5 or by incorporating information from both CMIP3 and CMIP5?

- **Successive Studies:** A study is initiated to perform more detailed analysis of a proposed project or plan that was previously analyzed at a lower level of detail—for example, a feasibility study is initiated for a project or plan for which an appraisal study has already been completed. The previous study used climate projection information from CMIP3. Should the new study continue to use CMIP3, or should the new study incorporate climate projection information from CMIP5, either replacing the projections from CMIP3 with projections from CMIP5 or by incorporating information from both CMIP3 and CMIP5?

As discussed in Sections 3.1.1 through 3.1.5, the climate science community has not determined that CMIP5 is a better or more reliable source of climate projection information than CMIP3 and, as a result, the WCRP suggests that CMIP5 be considered an addition to, rather than a replacement of, CMIP3 unless and until the climate science community determines otherwise. Based on this conclusion from the WCRP, it is not necessary to update ongoing or successive studies to use climate projection information from CMIP5 over information from CMIP3.

For new studies, an appropriate set of climate projections should be selected based on consideration of study needs and dataset attributes as discussed previously in this section.

3.2. Choosing between Global and Downscaled Climate Projections

When selecting the climate projection dataset for a given study, technical specialists on the study teams must choose whether to use global climate projections (sometimes called raw GCM projections) or to use projections that have been downscaled to a finer spatial resolution (i.e., downscaled climate projections).

Global climate projections may be appropriate for use in studies that do not require quantitative analysis of climate change impacts and that do not use climate projections to develop inputs to hydrology models or other resource models. In addition, global climate projections may be appropriate for studies that consider large spatial scales, such as projected changes in continental or global climate conditions. Global climate projections may also be appropriate for studies where large-scale weather phenomena are an important factor, such as projected changes in ocean-atmosphere teleconnections or mid-latitude storm tracks. Important aspects of the large-scale weather and climate phenomena may not be represented in downscaled projections or may be altered by the downscaling method. In these cases, study teams may consider using global projections, or joint use of both global and downscaled projections, to meet their specific study needs. It should be noted, however, that study teams must take care to assess how well the large-scale weather phenomena of interest are represented in GCMs prior to using GCM-based climate projections in their analysis.

By contrast, global climate projections likely are typically not appropriate for studies that require detailed, quantitative analysis of climate change and its impacts on water and environmental resources, including studies that involve the use of hydrology and other resource models to evaluate projected risks and impacts of climate change. As discussed in Section 2.2.3., the spatial resolution of GCMs is typically too coarse to use in most regional or basin-scale analyses, including analyses of how climate change will impact water supplies and demands. For this type of study, downscaled climate projections are likely to be more appropriate.

3.3. Choosing a Downscaled Climate Projection Datasets

Once a study team has determined that it will use downscaled climate projections, the technical specialists on the study team must then select which downscaled dataset is most appropriate with respect to their specific study objectives. In selecting a downscaled climate projection dataset, study teams should consider the general strengths and limitations of statistical versus dynamical downscaling methods, as well as the specific attributes of individual datasets.

This section outlines several important attributes of climate projection datasets that study teams should consider and provides a brief discussion of how each attribute typically compares between statistically and dynamically downscaled climate projection datasets. A general overview of statistical and dynamical downscaling methods is provided in Section 2.2.3., and specific attributes of individual downscaled projection datasets are described in Section 3.2.

3.3.1. General Dataset Attributes to Consider in Selecting a Downscaled Climate Projection Dataset

Table 1 provides a list of general dataset attributes that study teams should consider when selecting a downscaled climate projection dataset. Each of these attributes varies widely among available downscaled climate projection datasets, and each one may affect the applicability of a given downscaled dataset with respect to the specific objectives of any given study. When choosing a downscaled climate projection dataset, study teams should consider which attributes are most relevant to their study objectives and select a downscaled projection method and/or dataset whose attributes best meet the needs of their specific study.

Table 1: General Attributes of Downscaled Climate Projection Datasets

Attribute	Relevance to Study Objectives
Spatial Coverage	Does the dataset fully encompass the region of interest?
Spatial Resolution	Is the dataset's spatial resolution sufficient to meet the needs of the study?
Temporal Coverage	Does the dataset encompass the time period(s) required to meet the needs of the study?
Temporal Resolution	Is the dataset's temporal resolution (e.g., daily or monthly) sufficient to meet the needs of the study?
Available Scenarios/Projections	Does the dataset include a sufficient number of emissions scenarios and/or projections to meet the needs of the study?
Available Climate Variables	Does the dataset include the relevant climate variables needed to meet the needs of the study—e.g., does the dataset include all variables needed as inputs to the models used in the study? If the dataset does not include all input variables, is it acceptable to use alternate methods to estimate variables not provided by the dataset under future climate or to use inputs based on historical data for these variables?
Bias Correction	If relevant for the study, does the downscaling method include bias correction of GCM outputs?
Coherence among Climate Variables	If relevant for the study, does the downscaling method preserve the physical relationships (coherence) among climate variables?
Local-Scale Climate Feedbacks	If relevant for the study, does the downscaling method used by the dataset represent local-scale processes that affect the relationship between local-scale and large-scale climate conditions?

3.3.2. Comparison of General Attributes between Statistically and Dynamically Downscaled Climate Projection Datasets

As summarized in Section 2.2.3., downscaling methods fall into two broad categories: dynamical methods and statistical (non-dynamical) methods. Dynamical downscaling methods use finer-resolution regional climate models (RCM) to simulate the three-dimensional and multivariate atmospheric response to global climate change, nesting the RCM inside the GCM. By contrast, statistical downscaling methods use relationships between observed large-scale and finer-scale weather and climate conditions to downscale coarse-resolution GCM projections to finer resolution.

This section briefly discusses similarities and differences between the general attributes typical of statistical and dynamical downscaling datasets; differences are summarized in Table 2. While dynamical and statistical downscaling methods each exhibit a number of benefits and limitations, the attributes of a typical statically downscaled dataset differ from those of a typical dynamical downscaled dataset. Understanding these differences will help the technical specialists on a given study teams to make informed decisions when choosing the climate projection dataset for a given study.

Table 2: Comparison of General Attributes between Statistically and Dynamically Downscaled Climate Projection Datasets

Attribute	Statistical Downscaling	Dynamical Downscaling
Spatial Coverage	Depends on dataset	Depends on dataset
Spatial Resolution	Typically higher	Typically lower
Temporal Coverage	Typically longer	Typically shorter
Temporal Resolution	Similar or lower	Similar or higher
Available Scenarios/Projections	Typically more	Typically fewer
Available Climate Variables	Typically fewer	Typically more
Bias Correction	Typically yes	Typically no
Coherence among Climate Variables	Typically not preserved	Preserved by RCM
Local-Scale Climate Feedbacks	Typically not represented	Represented by RCM

Spatial Coverage: Spatial coverage depends on the individual dataset rather than whether the dataset is based on a statistical or dynamical downscaling method. Spatial coverage varies widely between downscaling datasets regardless of the overall downscaling method used. The publically available climate projection datasets summarized in Section 4.2. were selected in part based on their spatial domains encompassing the Western United States. However, several of these datasets encompass the entire CONUS and some include portions of southern Canada and northern Mexico.

Spatial Resolution: The spatial resolution of statistical downscaling methods is primarily limited by the spatial resolution of available historical climate observations. By contrast, the spatial resolution of dynamically downscaled datasets is limited primarily by the computer resources available to run the RCM(s) used to dynamically downscale GCM outputs. The spatial resolution of statistically downscaled datasets typically ranges from approximately 4 km ($^{1}/_{24}$° latitude by $^{1}/_{24}$° longitude) to approximately 12 km ($^{1}/_{8}$° latitude by $^{1}/_{8}$° longitude). The spatial resolution of dynamically downscaled datasets is typically on the order of 25-50 km ($^{1}/_{4}$°-$^{1}/_{2}$° latitude by $^{1}/_{4}$°-$^{1}/_{2}$° longitude) for datasets covering the CONUS, whereas dynamically downscaled datasets covering smaller regions have resolutions as high as 15 km ($^{1}/_{10}$° latitude by $^{1}/_{10}$° longitude). Hence the spatial resolution of statistically downscaled datasets is typically greater than those of dynamically downscaled datasets for the publically available datasets discussed in Section 4.2.

Temporal Coverage: Temporal coverage of statistically downscaled climate projections is primarily limited by the temporal coverage of the GCM outputs. By contrast, temporal coverage of dynamically downscaled datasets is strongly limited by the computer resources available to run the RCM(s) used to dynamically downscale GCM outputs. As a result, dynamically downscaled datasets often contain projections for selected periods of the 20th and 21st centuries (e.g., one 20-year period from the late 20th century and two or three 20-year periods from the 21st century). By contrast, statistically downscaled climate projection datasets commonly encompass a continuous period from the mid- or late-20th century through the end of the 21st century. However, temporal coverage ultimately depends on the individual downscaled dataset.

Temporal Resolution: Statistical downscaling methods are typically developed to operate on a monthly or daily timescale and are often only valid at the intended timescale. As a result, statistically downscaled projections are typically available either daily or monthly resolution. By contrast, the RCMs used to produce dynamically downscaled projections simulate regional climate using a much shorter model timestep, often as short as just a few minutes. The temporal resolution of dynamically downscaled climate projections depends on the data archiving interval specified by the modeling team who developed the downscaled projections. The archive interval is limited by the computer storage available to host the dataset and typically ranges from 3 to 6 hours for primary climate variables, with daily or monthly outputs for secondary variables. Dynamically downscaled climate projection datasets therefore often offer higher temporal resolution than statistically downscaled datasets.

Available Scenarios/Projections: Dynamical downscaling is extremely computationally expensive compared to statistical downscaling methods. As a result, dynamically downscaled climate projection datasets often contain fewer emissions scenarios and individual climate projections than statistically downscaled datasets. The smaller number of scenarios and projections typical of dynamical downscaling datasets may limit the range of uncertainty represented by these datasets.

Available Climate Variables: Statistical downscaling methods are based on relationships between large-scale and finer-scale climate conditions, where the relationship between large- and small-scale conditions are developed based on historical observations. Statistical downscaling methods, therefore, depend on the availability of historical observations for each variable that is downscaled. As a result, many statistically downscaled datasets provide data for only temperature and precipitation, while some provide additional variables relevant to the hydrologic cycle such as wind speed, humidity, and solar radiation. Dynamically downscaled climate projections are produced by RCMs that simulate the complete regional climate system, including a multitude of climate and hydrologic variables in the atmosphere and at the land surface. While RCMs simulate virtually all relevant climate variables, the variables available from any given dynamically downscaled dataset vary widely, depending on which variables were selected to be archived as part of the dataset. It should be noted that empirical methods are available to estimate some variables if they are not provided by a given dataset—for example, Reclamation 2015 estimated solar radiation and humidity under future climate based on projected maximum and minimum daily temperature.

Bias Correction: Statistical downscaling methods generally incorporate a bias correction step that adjusts GCM output so that simulated historical climate conditions match observed historical conditions (see Section 2.2.3.). Biases are similarly removed from simulated future climate conditions by assuming that the characteristics of model bias under future climate conditions are the same as under historical conditions. Dynamically downscaled datasets, by contrast, often do not include bias correction: raw GCM outputs are used as inputs to a RCM, and the RCM then inherits any biases exhibited by the GCM. Lack of bias correction may inhibit the use of dynamically downscaled climate projections as direct inputs to hydrologic models and other resource models.

Coherence among Climate Variables: Statistical downscaling methods typically downscale each climate variable independently, without considering relationships between climate variables. Dynamical downscaling, by contrast, uses RCMs to simultaneously downscale all relevant climate variables. Dynamical downscaling therefore preserves the coherence among climate variables, whereas statistical downscaling may not.

Local-Scale Climate Feedbacks: Statistical downscaling methods use relationships between observed large-scale and finer-scale weather and climate conditions to downscale large-scale GCM results to a finer resolution. This approach assumes that observed relationships between large-scale and finer-scale weather and climate remain valid under future climate conditions. As a result, statistical downscaling methods do not account for potential local-scale feedbacks that may alter the relationship between large-scale and finer-scale weather and climate conditions as the climate changes, such as feedbacks between changes in snow covered area or soil moisture content and local temperature, winds, humidity, and precipitation. Dynamical downscaling using RCMs does allow for local-scale feedbacks to affect the local weather and climate response to changes in large-scale climate.

3.3.3. Project-Specific Downscaling to Support Study Needs

In some cases, after reviewing the existing publically available downscaled climate projection datasets, study teams may find that none of the existing datasets meet the specific needs of their study. For example, downscaled climate projections may not be available for studies focusing on areas outside of the CONUS or other regions where downscaled projections have been previously developed. In other cases, study teams focusing on extreme climate events (e.g., extreme precipitation) may determine that none of the available downscaled datasets are suitable for their analysis due to potential limitations of statistical downscaling methods in capturing changes in climate extremes, insufficient coverage or resolution of dynamical downscaling datasets, and/or biases in dynamically downscaled climate projections. Alternatively, study teams may determine that existing datasets do not sufficiently represent aspects of weather and climate that are important for their study region, such local topography (e.g., narrow valleys), coastal winds, or local fog and/or clouds that significantly affect evapotranspiration in the study area.

In such cases, study teams may consider conducting project-specific downscaling of CMIP3 or CMIP5 climate projections to support the specific needs of their study. Project-specific downscaling involves applying a verified and published statistical method or RCM to downscale global climate projections from the CMIP3 or CMIP5 multi-model dataset over the study region. It should be noted that the time and budget needed to conduct project-specific downscaling is significantly greater than that needed to use an existing dataset. As a result, study teams must clearly justify the choice to conduct project-specific downscaling based on the limitations of existing downscaled climate projection datasets with respect to their specific study objectives and the ability of the proposed project-specific downscaling to overcome those limitations.

3.4. Choosing a Method to Select Climate Projections for Use in a Detailed Analysis

As summarized in Section 5., several methods have been developed to select a subset of climate projections for use in a detailed analysis when schedule and budget constraints prohibit detailed analysis of all available projections from the climate projection dataset chosen for use in a given study. These methods fall into two general categories:

- **Uncertainty-based**: selecting projections based on sampling the range of uncertainty in projected future climate

- **Performance-based:** selecting models based on their performance in simulating observed historical climate conditions

Uncertainty-based and performance-based methods have both been widely used in climate change impact and adaptation studies. This section discusses important assumptions and limitations to consider when choosing a selection method.

In addition to these two general categories of selection methods, this section discusses considerations that arise when the climate projection dataset chosen for use in a given study contains multiple climate projections produced using the same combination of GCM and emissions scenario.

3.4.1. Methods Based on Sampling Range of Uncertainty

Section 5.1 discusses methods for selecting climate projections based on sampling the range of uncertainty in projected climate conditions from a given climate projection dataset. In general, uncertainty-based methods are preferred in cases where study teams have an interest in characterizing uncertainty in future conditions and developing adaptation strategies that are robust under a broad range of potential future conditions.

It should be noted, however, that climate projection information resources are not designed to provide an accurate and unbiased estimate of the range of uncertainty in future climate projections (Tebaldi and Knutti 2007, Knutti et al. 2013, and Sanderson et al. 2015). There are three primary sources of uncertainty regarding future climate conditions: uncertainty in the trajectory (amount and timing) of anthropogenic greenhouse gas and aerosol emissions; uncertainty in the climate system response to anthropogenic emissions; and uncertainty in how natural emissions (e.g., volcanic eruptions) and natural (unforced) climate variability may act to mask or amplify the climate response to anthropogenic forcing (Hawkins and Sutton 2009 and Mote et al. 2011). Climate projection information resources such as the CMIP3 and CMIP5 multi-model datasets and corresponding downscaled projection datasets partially represent each of these uncertainties. For example, uncertainty in future emissions is partially represented by the range of emissions scenarios considered in each dataset; however, actual future emissions may diverge from the range of scenarios considered. As a result, sampling the range of projected climate change based on any given climate projection dataset is likely to underestimate the full range of potential future climate conditions.

Another important consideration regarding selection methods based on sampling the range of uncertainty in projected future climate is the potential influence of similarities between different models and projections within a given dataset. Some projection datasets include multiple projections from the same combination of model and emissions scenario, differing only in the initial conditions at the start of the projection (see Section 3.4.3.). Because each model produces a unique estimate of climate sensitivity to anthropogenic emissions, including more simulations from some models than others may bias the range of projected changes and therefore the projection selection process. For example, consider a hypothetical dataset that includes projections based on two climate models under one emissions scenario. One of the model exhibits a high sensitivity to anthropogenic emissions and one that exhibits a low sensitivity. If five projections are available from one model and one projections are available from the other, then the range of projected change will be skewed towards the model with a larger number of projections. The situation is more complicated for the CMIP3 and CMIP5 multi-model datasets given the larger number of models, emissions scenarios, and individual climate projections, but the same principle applies: the range of projected climate change is potentially skewed towards the models and emissions scenarios for which more projections are available.

In addition, studies suggest that similarities between GCMs themselves may bias estimates of uncertainty based on multi-model datasets (Tebaldi and Knutti 2007, Knutti et al. 2013, and Sanderson et al. 2015). While any given GCM provides a unique representation of the overall climate system, many GCMs share various model components. For example, two GCMs may have different atmospheric components but share a common ocean component. Similarly, even when different components are used, models often share many underlying assumptions and parameterizations. These common components, assumptions, and parameterizations result in similarities between models. As a result, the probability distribution of projected climate change may be biased due to the lack of independence between GCMs—in other words, a multi-model ensemble does not represent a random sample of projected climate conditions.

With respect to water resources, planning, and environmental analyses, the underlying objective of selecting climate projections for detailed analysis based on sampling the range of uncertainty is often to consider a range broad range of plausible future conditions. In this context, the lack of independence between models and projections within a given dataset does not impact the underlying objective. As a result, it remains common practice in water resources, planning, and environmental analyses to consider all available projections from a given dataset and to treat all models as independent when selecting a subset of projections

3.4.2. Methods Based on Evaluation of Model Performance

Section 5.2. discusses methods for selecting climate projections based on evaluation of model performance with respect to simulation of observed historical climate conditions. Performance-based methods may be preferred in cases where study teams have a strong interest in ensuring that specific weather or climate phenomena relevant to the study region and/or study objectives are well represented in the GCMs used to develop climate projection information used in the study. Study teams considering future floods or droughts in some regions, for example, may want to ensure that the GCMs used to develop climate projections for that study are able to represent important weather phenomena associated with floods or droughts in that region—e.g., representation of the El Niño-Southern Oscillation with respect to floods and droughts in California and the Pacific Northwest, or representation of the North American monsoon with respect to floods in the arid Southwest.

While selection methods based on evaluation of model performance have been used in previous water resources and environmental planning efforts, recent studies have demonstrated several potential limitations associated with these methods. First and foremost, several studies suggest that model performance in simulating historical weather and climate are not a clear indicator of model credibility in projecting future climate change (Reifen and Toumi 2009, Knutti et al. 2010, and IPCC 2013). IPCC 2013 notes that "*confidence in climate model projections is based on physical understanding of the climate system and its representation in climate models, and on a demonstration of how well models represent a wide range of processes and climate characteristics*." By contrast, attempts to rank or weight the relative credibility of different GCMs has shown that there is no clear relationship between a model's performance in simulating historical climate and its projection of future climate change (Knutti et al. 2010):

> *"Correlations between model simulated historical trends, variability or current mean climate state…on the one hand, and future projections for observable climate variables on the other hand, are often predominately weak. For example, the climate response in the 21st century does not seem to depend in an obvious way on the simulated pattern of current temperature."*

These studies indicate that while it is important to verify that climate models provide a realistic representation of the global climate system, the relative difference in models' performance is not an indicator of the relative credibility or accuracy of projected of future climate change.

In addition to challenging the underlying premise that model performance is not related to the credibility or accuracy of future climate projections, several studies have identified practical challenges in using model performance metrics to select a subset of models for use in a detailed analysis (Gleckler et al. 2008, Brekke et al. 2008, and see Section 9.8 of IPCC 2013 for additional discussion). In particular, model performance—along with the relative ranking of performance among models—is often strongly dependent on the region, metric, and time period selected for analysis: "*inevitably, some models perform better than others for certain climate variables, but no individual model clearly emerges as 'the best' overall*" (IPCC 2013). As a result, small changes in the metrics used to evaluate model performance, or the region and time period over which metrics are calculated, can significantly alter the relative performance ranking between models. For example, a given model's performance ranking based on temperature may be significantly different than its ranking based on precipitation; alternatively, model rankings over the period 1970-1999 may be significantly different than rankings based on evaluation over the longer period 1950-1999. These results indicate that the relative performance ranking of models based on a limited number of performance metrics is not a robust criterion for model selection.

It is also important to note that selection methods based on evaluation of model performance focus on selection of GCMs based on their relative performance ranking. However, these methods do not facilitate selection of individual projections. Where multiple projections are available for a given combination of GCM and emissions scenario (i.e., where multiple projections were produced by varying the initial conditions at the start of the projection), study teams must identify additional criteria for selecting individual projections for use in a detailed analysis. These additional criteria may be based on sampling the range of uncertainty in projected climate change from the selected models or may focus on some alternative criteria developed by the study team.

3.4.3. Consideration of Multiple Projections from a Single Combination of GCM and Emissions Scenario

As noted above, some climate projection datasets include multiple projections from a single combination of model and emissions scenario, where each simulation differs from the others only in the initial conditions at the start of the projection. In other words, the GCM and all time-varying inputs are identical, including atmospheric concentrations of greenhouse gases and aerosols, but the distribution of mass and energy (i.e., temperature, humidity, pressure, and other variables) are different at the start of each projection. If the climate projection dataset chosen for a given study includes multiple projections from a single combination of GCM and emissions scenario, technical specialists on the study team must determine how to treat these projections when selecting a subset for use in a detailed analysis.

Modeling teams often produce multiple simulations using the same GCM and emissions scenario—but with different initial conditions—to evaluate the sensitivity of projected weather and climate conditions to changes in these initial conditions. Changes in the initial conditions at the start of a simulation affect day-to-day weather conditions, which in turn affects natural climate variability on seasonal to decadal timescales. By conducting multiple climate projections using the same GCM and emissions scenario, climate scientists can distinguish between naturally-occurring low-frequency climate variability and climate change resulting from anthropogenic changes in atmospheric composition.

Day-to-day weather conditions at any given place and time are largely determined by the complex and highly non-linear processes that govern atmospheric dynamics (Wallace and Hobbs 2006). These processes cause the atmosphere to be highly unstable: small changes in the state of the atmosphere (e.g., small changes in the distribution of mass and energy) grow rapidly over time. One important implication of this unstable behavior is that the day-to-day evolution of weather conditions generally cannot be accurately predicted more than seven to ten days in advance. Imperfect observations of the atmosphere lead to errors in the initial state at the start of a forecast. The complex and highly non-linear nature of atmosphere dynamics subsequently causes these errors to grow rapidly over the forecast period, resulting in large uncertainty in predicted weather conditions just hours or days into the forecast. While our incomplete understanding of atmospheric processes contributes to forecast errors, many studies suggest that even if weather prediction models perfectly represented all aspects of the atmosphere, infinitesimally small errors in model initial conditions at the start of a forecast would still limit our ability to forecast day-to-day weather conditions more than two weeks in advance (for example, see Epstein 1988 and Palmer 2000 for discussion of the fundamental limits of predictability in weather and climate).

This sensitivity of day-to-day weather to changes in initial conditions also has implications for projections of long-term climate change. Interactions between rapidly-changing atmospheric conditions and slowly-varying ocean and land surface conditions contribute to climate variability on interannual and decadal timescales. Low-frequency (decadal) climate variability can result in apparent trends in temperature and precipitation. These trends may persist for several decades before abating or reversing. As a result, it is difficult to distinguish between low-frequency climate variability and anthropogenic climate change in a single GCM projection (see Section 2.1. for discussion of the difference between climate variability and climate change). However, the timing and magnitude of apparent trends resulting from low-frequency variability will be different between simulations starting from different initial conditions. By contrast, trends resulting from anthropogenic climate change are less sensitive to initial conditions. Analysis of multiple climate projections from a single combination of GCM and emissions scenario can thus be used to distinguish between low-frequency climate variability and climate change.

It is important to note that multiple projections from a given GCM and emissions scenario—but with different initial conditions—are not independent. Attempts to characterize the magnitude and uncertainty of projected climate change may therefore be biased by considering different numbers of projections from each combination of model and emissions scenario. For example, one GCM may project a larger change in temperature under a given emissions scenario than another GCM. If a dataset includes five projections under this scenario from the first GCM and only one under the second, averaging over all available projections would result in an average projected change that is larger than if each GCM contributed the same number of simulations.

When selecting climate projections for use in a detailed analysis, however, each individual projection is considered equally valid. If the study team's objective is to consider a broad range of future climate conditions, it is reasonable to sample the full range of projections without accounting for differences in the number of projections from each combination of GCM and emissions scenario.

4. Climate Projection Datasets

The summaries provided in this section are intended to aid *technical specialists* in selecting an appropriate climate projection information resource to support climate change projections and analysis for a particular study.

The scientific community has developed a vast amount of information regarding projected future climate conditions, including multiple datasets[10] containing climate projections from one or more global climate models (GCM) under one or more emissions scenarios representing possible future trajectories of global greenhouse gas and aerosol emissions. In addition to global projections, datasets have been developed to provide projections of future climate at finer spatial and temporal scales based on downscaling global projections over various regions. These datasets constitute the climate projection information resources available to Reclamation study teams.

Climate projection datasets vary substantially—for example, covering different geographical areas and time periods, and with different spatial and temporal resolutions. The models, methods, and assumptions used to develop climate projection information also vary widely between resources. These differences can have important implications for applying a given information resource to a specific study, including the range of projected future climate conditions and corresponding impacts on water and environmental resources. In addition, differences between datasets may affect the method options available to incorporate projection information into a given analysis.

This section summarizes several currently available and widely used climate projection information resources.

- Section 3.1. and Table 3.1. summarize global climate projection datasets based on GCM projections of future climate conditions

- Section 3.2. and Table 3.2. summarize regional climate projection datasets based on downscaling and/or bias correction of GCM projections.

[10] Climate projection datasets consist of set of numerical data files. Each value in a given file represents the value of a specific climate variable—precipitation, temperature, pressure, humidity, etc.—at a specific time and location. Global and downscaled climate projections are typically provided in the form of gridded data files, where values are organized as a three-dimensional array with dimensions representing latitude, longitude, and time. Some variables such as air pressure may be represented as a four-dimensional array, where the fourth dimension represents height above the earth's surface. The data structure, file format, units, and other attributes vary between datasets; dataset attributes are defined in the corresponding dataset documentation.

4.1. Global Climate Projection Datasets

Global Climate Models (GCM) are the primary tools used to develop projections of future climate conditions. As summarized in Section 2.2,. GCMs simulate the physical processes within and between the atmosphere, oceans, land surface, and cryosphere that govern the global climate system. Notably, GCMs are widely used to simulate changes in the global climate system in response to changes in atmospheric composition, including changes in greenhouse gas and aerosol concentrations. GCMs simulate climate processes across the entire globe. Due to computational constraints, however, GCMs typically simulate climate processes at relatively coarse spatial resolution. For the current generation global climate projections for the 21st century, GCMs are typically configured such that each model grid cell represents an area on the order of 10,000 km^2 (i.e., an area spanning ~100 km east-west by ~100 km north-south).

The scientific community currently uses two primary GCM-based climate projection datasets: the CMIP Phase 3 (CMIP3) Multi-Model Dataset, completed in 2007, and the CMIP Phase 5 (CMIP5) Multi-Model Dataset, completed in 2013. Both datasets were coordinated and facilitated by the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project (CMIP). It should also be noted that there was no CMIP Phase 4; the CMIP numbering was modified to coincide with the corresponding IPCC assessment reports to avoid confusion.

Since its inception in 1995, CMIP has played a central role in coordinating international modeling efforts focused on better understanding the global climate system, including past, present, and future climate changes resulting from natural (unforced) climate variability and from changes in radiative forcing (e.g., anthropogenic changes in greenhouse gas concentrations) (WCRP 2015). An important focus of CMIP is to facilitate broader analysis and application of global climate projections across the climate science research community by making climate model data available to scientists outside of the major modeling groups who develop and run GCMs. To this end, CMIP provides standards and guidelines that allow for comparing GCM results across the many GCMs developed by scientists and research groups from around the world. Beginning with CMIP3, the U.S. Department of Energy's Program for Climate Model Diagnostics and Intercomparison (PCMDI) has worked closely with CMIP to compile GCM datasets from modeling centers around the globe and make them freely available to the scientific community (PCMDI 2015). The multi-model datasets developed by each phase of CMIP constitute the primary climate projection information resources used by the global climate science community, including the IPCC, to evaluate climate change and its potential impacts.

Climate projections available in the CMIP3 and CMIP5 multi-model datasets are briefly described below and summarized in Table 3. Table 3 does not include historical simulations (e.g., pre-industrial and 20th century) or idealized emissions scenarios (e.g., 1% increase in CO_2 per year until doubling). In addition, Table 3 does not include the three SRES "marker" scenarios that are not included in the CMIP3 multi-model dataset (SRES scenarios A1T, A1FI, and B2).

Table 3. Summary of 21st Century Global Climate Projections in the CMIP3 and CMIP5 Multi-Model Datasets

	CMIP3	CMIP5
Web Address	http://cmip-pcmdi.llnl.gov/cmip3_overview.html	http://cmip-pcmdi.llnl.gov/cmip5/index.html
Emissions Scenarios	***SRES A2***: High emissions scenario characterized by globally fragmented development and slower economic growth ***SRES A1B***: Medium emissions scenario characterized by rapid economic growth and a balance between fossil and alternative energy sources ***SRES B1***: Low emissions scenario characterized by rapid changes in economic structures, with reductions in material intensity and introduction of clean and resource-efficient technologies	***RCP 8.5***: "Business as usual" scenario. High emissions scenario where greenhouse gas concentrations continue to rise unchecked ***RCP 6.0:*** "Medium emissions scenario by 2080" assumes a mitigation strategy where greenhouse gas emissions peak around 2080 and decline thereafter ***RCP 4.5***: "Medium emissions scenario by 2040" assumes a mitigation strategy where greenhouse gas emissions peak around 2040 and decline thereafter ***RCP 2.6: "***High mitigation" scenario, considered the low emissions scenario, assumes that greenhouse gas emissions peak between 2010 and 2020 and decline substantially thereafter
Number of GCMs	23	61
Model Resolution (Atmospheric Grid)	Latitude: 1.125° – 5.0° Longitude:1.125° – 4.0°	Latitude: 0.56° – 3.44° Longitude:0.56° – 3.75°

4.1.1. CMIP Phase 3 Multi-Model Dataset

CMIP3 was the climate modeling community's first large-scale effort to coordinate a set of climate model simulations that "could be performed by as many modeling groups as possible with state-of-the-art global coupled[11] climate models" and with results compiled and made available to the broader research community for analysis (IPCC 2007 [Physical Science]). The CMIP3 simulations include a total of eleven emissions scenarios, each of which represents a different set of time-varying atmospheric concentrations of greenhouse gasses and aerosols. Four of these scenarios served as the primary basis for analyzing future climate change in the IPCC Fourth Assessment Report (IPCC 2007 [Physical Science] and IPCC 2007 [AR4 Impacts]), including one scenario corresponding to historical emissions over the 20th century and three scenarios representing plausible trajectories of future emissions over the 21st century (SRES scenarios B1, A1B, and B2). The range of emissions scenarios considered in CMIP3 is summarized below:

- Constant atmospheric composition (100-year minimum simulation period) based on pre-industrial conditions

- Time-varying 20th century atmospheric composition (1860-2000) based on historical trajectories of natural (e.g., volcanic) and human (e.g., industrial greenhouse gas and aerosol) emissions

- Time-varying 21st century atmospheric composition (2001-2100) based on hypothetical trajectories of human greenhouse gas and aerosol emissions under selected emissions scenarios from the IPCC 2000 (SRES) (see Section 2.2.1. for additional discussion):
    - B1 (low emissions)
    - A1B (medium emissions)
    - A2 (high emissions)

- Constant atmospheric composition (100-year minimum simulation period) based on observed conditions for the year 2000, conditions under scenario SRES B1 for the year 2100, and conditions under scenario SRES A1B for the year 2100

[11] In the context of global climate models, the term *coupled* refers to models that represent interactions between the atmosphere and the underlying land, ocean, and ice through exchanges of energy (heat), moisture, and momentum. For example, a coupled climate model includes an ocean model that can simulate heat uptake by the oceans from the atmosphere and subsequent effects on ocean circulation and sea surface temperatures; by contrast, an atmosphere-only (un-coupled) climate model represents ocean conditions as a model input and does not simulate the ocean's response to atmospheric conditions. All climate models in the CMIP3 Multi-Model Dataset are coupled climate models. Additional discussion of coupled climate models is provided at World Meteorological Organization's website: https://www.wmo.int/pages/themes/climate/climate_models.php.

- Constant and time-varying atmospheric compositions under various idealized scenarios

CMIP3 model results were compiled and made available for analysis by the broader research community. In total, the CMIP3 Multi-Model Dataset includes model outputs from a total of 23 GCMs from 16 modeling centers representing 12 different countries. CMIP3 ultimately became "*the largest international global coupled climate model experiment and multi-model analysis ever attempted*" (IPCC 2007 [Physical Science]).

Simulations of pre-industrial climate, 20th century climate, and 21st century climate under scenarios B1, A1B, and A2 were provided by nearly all of the 23 GCMs that contributed to the CMIP3 Multi-Model Dataset.[12] Additional simulations under constant and idealized atmospheric forcings were provided by some but not all models. Several models provided multiple simulations for some emissions scenarios. In these cases, individual simulations incorporate identical atmospheric forcings as specified by the scenario and differ only in their initial conditions at the start of the simulation. As atmospheric processes are sensitive to small perturbations in atmospheric conditions, the use of different initial conditions results in a different evolution of natural (unforced) climate variability in each simulation. Simulation of the same simulations (i.e., identical external forcings) from different initial conditions thus allows for comparison of natural[13] (unforced) versus anthropogenic[14] (forced) climate variability and change (IPCC 2007 [Physical Science] and Solomon et al. 2011).

CMIP3 simulations of 20th and 21st century climate have been widely used to diagnose and attribute historical climate variability and change and to assess potential impacts of climate change over the 21st century, including impacts on water and environmental resources at global and regional scales (e.g., see IPCC 2007 [Physical Science] and IPCC 2007 [AR4 Impacts]). In particular, simulations of 21st century climate under the SRES B1, A1B, and A2 emissions scenarios constituted the primary source of climate projection information available to scientists, engineers, planners, and decision makers around the world at the time of their release (IPCC 2007 [Physical Science] and IPCC 2007 [AR4 Impacts]). (See Section 2.2.1. of this report for a brief summary of emission scenarios).

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[12] Note that SRES scenarios A1T, A1FI, and B2 are not included in the CMIP3 multi-model dataset.

[13] Natural or unforced climate variability and change result from "*internal interactions between components of the climate syste*m" (IPCC 2007 [Physical Science]).

[14] Anthropogenic or forced climate variability and change result from human-caused changes to one or more component of the global climate system, including human-caused greenhouse gas and aerosol emissions and changes in land cover (e.g., deforestation) (IPCC 2007 [Physical Science]).

4.1.2. CMIP Phase 5 Multi-Model Dataset

CMIP5 was initiated shortly after the completion of CMIP3 and the related IPCC Fourth Assessment Report (AR4). A new set of coordinated model simulations for CMIP5 was finalized at an international meeting of the WCRP Working Group on Climate Modeling in September 2008 with input from more than 20 climate modeling centers from around the world. CMIP5 emissions scenarios were developed specifically to address scientific questions that arose as part of the AR4 assessment process, as well as to improve scientific understanding of the global climate system and to provide projections of future climate change for use in evaluating climate change impacts by scientists, policy makers, and decision makers (Taylor et al. 2009, Taylor et al. 2012, and IPCC 2013). CMIP5 was developed in part to contribute to the scientific basis for the IPCC Fifth Assessment Report (AR5), published in 2013.

Similar to CMIP3, CMIP5 defines a standard set of simulations and scenarios to address specific scientific questions. Key objectives guiding the development of CMIP5 scenarios include (Taylor et al. 2009 and Taylor et al. 2012):

- Evaluate how well climate models are able to simulate recent observed climate conditions, including seasonal, interannual, and multi-decadal variability as well as multi-decadal trends

- Develop climate projections of future climate change on near-term (through 2035) and long-term (through 2100) timescales

- Facilitate improved understanding of inter-model differences in projections of future climate, including differences in key feedback processes (for example, cloud radiative feedbacks[15] and carbon cycle feedbacks[16])

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[15] The term *cloud radiative feedbacks* refers to the interdependence between clouds and the atmospheric energy balance. The atmospheric energy balance affects air temperature, circulation, and movement of water vapor in the atmosphere. These factors in turn affect the formation of clouds. The occurrence and properties of clouds subsequently affect the amount of solar radiation reflected by and the amount of infrared radiation absorbed by the atmosphere, which in turn affects the atmospheric energy balance.

[16] The term *carbon cycle feedback* refers to the interdependence between the atmospheric concentration of carbon dioxide, global climate, and biogeochemical processes that govern the exchange of carbon between the atmosphere, land, and ocean: changes in atmospheric concentration of carbon dioxide affect global climate, including temperature and precipitation patterns; changes in precipitation and temperature affect biogeochemical processes, including metabolic and weathering processes that result in uptake or release of carbon from land and ocean systems; changes in carbon uptake and release affect the atmospheric concentration of carbon dioxide, which in turn affects global climate.

In contrast to CMIP3, which focuses on long-term projections of future conditions through the end of the 21st century, CMIP5 includes two sets of projections:

- **Near-term projections of the next few decades (through 2035).** Near-term projections are designed to evaluate model skill in forecasting climate change on timescales of 10-30 years, when initial states may exert some influence on climate trends through their influence on natural (unforced) low-frequency climate variability (Taylor et al. 2009).

- **Long-term projections through the end of the 21st century (through 2100).** Long-term projections are designed to evaluate the climate system response to external forcing by anthropogenic emissions of greenhouse gases and aerosols under specified emissions scenarios.

CMIP5 simulations of 20th and 21st century climate served as the primary scientific basis for the IPCC Fifth Assessment Report (AR5) and continue to be analyzed by the scientific community. Similar to the CMIP3 simulations, CMIP5 simulations are being used to diagnose and attribute historical climate variability and change and to assess potential impacts of climate change over the 21st century (e.g., see IPCC 2013, IPCC 2014 [AR5 Impacts]). CMIP5's long-term projections currently constitute the most current resource for global climate projection information. Analogous to CMIP3, four of the long-term projections served as the primary basis for analyzing future climate change, including one scenario corresponding to historical emissions over the 20th century and three scenarios representing possible trajectories of future emissions over the 21st century (RCPs 4.5, 6.0, and 8.5; see Section 3.1.2. for discussion of RCP emissions scenarios).

The CMIP5 Multi-Model Dataset of long-term climate projections includes global climate projections from a total of 61 GCMs from 27 modeling centers representing 15 different countries (PCMDI 2015). Simulations of pre-industrial climate, 20th century climate, and 21st century climate under RCPs 4.5 and 8.5 were provided by nearly all of the participating models. Additional simulations of 21st century climate under RCPs 2.6 and 6.0 were also provided by many participating models. Similar to CMIP3, additional simulations under constant and idealized atmospheric forcings were provided by some but not all models. Like CMIP3, several models provided multiple simulations for selected scenarios to allow comparison of natural (unforced) versus anthropogenic (forced) climate variability and change.

4.2. Downscaled Climate Projection Datasets

While dynamical and statistical downscaling methods each exhibit a number of strengths and limitations, previous research suggests that neither dynamical nor statistical downscaling methods are inherently more reliable than the other, and that technical teams should aim to select a downscaling method that is appropriate for their specific study objectives.

While GCMs represent the primary tools used to develop climate projection information, the coarse spatial resolution and inherent bias[17] of GCMs effectively prohibit direct application of GCM results for hydrology and water resources applications, including analyses of climate change impacts on water availability. To use GCM outputs—e.g., simulated precipitation and temperature at the native GCM resolution—as inputs to hydrologic and other resources models, GCM outputs must first be downscaled or spatially disaggregated to a finer spatial resolution that is consistent with those models (see Section 2.2.3).. In addition, GCM outputs may be adjusted to remove biases between simulated and observed climate conditions (see Section 2.2.3.).

Numerous methods have been developed to downscale climate projection information for use in climate impact and adaptation studies, including studies in the water sector as well as other environmental and resource management sectors. As summarized in Section 2.2.3., downscaling methods generally fall into one of two broad categories:

- Dynamical methods use finer-resolution regional climate models (RCM) to simulate the three-dimensional and multivariate response to global climate change.
- Statistical (non-dynamical) methods encompass a broad range of approaches that rely on observed historical weather and climate as the basis for deriving finer-resolution climate projections from coarse-resolution global climate projections. Statistical methods range from simple change factors and transfer functions, to regression models, to more physically based weather generators (Wilby et al. 2004).

This section briefly describes eleven downscaled climate projection datasets that are publically available and have been previously used to evaluate the impacts of climate change on hydrology and water resources in the Western United States.

[17] The term *bias* refers to differences between simulated and observed climate conditions—e.g., differences between simulated and observed mean annual temperature or precipitation over a region of interest. See Section 2.2.3.

Details of each downscaled dataset are summarized in Table 4. All of the datasets summarized here were developed by statistically or dynamically downscaling GCM-based global climate projections from the CMIP3 and/or CMIP5 multi-model datasets over part or all of the CONUS. Datasets differ by:

- Downscaling method
- Spatial and temporal domains and resolutions
- Combinations of climate variables
- Sets of GCM projections

While the datasets summarized here represent several of the more widely used downscaled climate projection datasets for the Western United States, it should be noted that these datasets represent a relatively small sample of the downscaling methods available in the scientific literature. The statistically downscaled datasets, in particular, represent on a small subset of available statistical downscaling methods. However, while many other downscaling methods have been documented in the scientific literature, these other methods have not been used to develop publically-accessible datasets of downscaled climate projections.

The datasets summarized in this document were selected based on their:

- Spatial domains encompassing the Western United States
- Availability through publically-accessible websites
- Prior use in water resources impact assessments and planning studies

Comprehensive discussion of downscaling methods presented in the scientific literature is beyond the scope of this document.

Table 4. Summary of Downscaled Climate Projection Datasets

	Spatial Domain	Spatial Resolution	Temporal Domain	Temporal Resolution	Climate Variables	Projections	GCMs	Emission Scenarios
CMIP3 BCSD	CONUS	$^1/_8$° by $^1/_8$°	1950-2099	Monthly	Total precipitation [mm] Mean surface air temperature [°C]	112	16	SRES B1 SRES A1B SRES A2
CMIP5 BCSD	CONUS	$^1/_8$° by $^1/_8$°	1950-2099	Monthly	Total precipitation [mm] Mean surface air temperature [°C] Maximum surface air temperature [°C] Minimum surface air temperature [°C]	234	37	RCP 2.6 RCP 4.5 RCP 6.0 RCP 8.5
CMIP3 BCCA	CONUS	$^1/_8$° by $^1/_8$°	1961-2000; 2046-2065; 2081-2100	Daily	Total precipitation [mm] Maximum surface air temperature [°C] Minimum surface air temperature [°C]	53	9	SRES B1 SRES A1B SRES A2
CMIP5 BCCA	CONUS	$^1/_8$° by $^1/_8$°	1950-2099	Daily	Total precipitation [mm] Maximum surface air temperature [°C] Minimum surface air temperature [°C]	134	20	RCP 2.6 RCP 4.5 RCP 6.0 RCP 8.5
CMIP5 MACA – METDATA v1	Western US (31°-49°N, 125°-103°W)	$^1/_{24}$° by $^1/_{24}$°	1950-2100	Daily	Precipitation at surface [kg/m2/s] Maximum air temperature near surface [°C] Minimum air temperature near surface [°C] Maximum relative humidity near surface [-] Minimum relative humidity near surface [-] Mean specific humidity near surface [-] Mean downward shortwave radiation [W/m^2] Mean wind speed near surface [m/s] Mean eastward component of wind [m/s] Mean northward component of wind [m/s]	20	20	RCP 2.6 RCP 8.5
CMIP5 MACA – METDATA v2	CONUS	$^1/_{24}$° by $^1/_{24}$°	1950-2099	Daily	Precipitation at surface [kg/m2/s] Maximum air temperature near surface [°C] Minimum air temperature near surface [°C] Maximum relative humidity near surface [-] Minimum relative humidity near surface [-] Mean specific humidity near surface [-] Mean downward shortwave radiation [W/m^2] Mean eastward component of wind [m/s] Mean northward component of wind [m/s]	20	20	RCP 2.6 RCP 8.5

	Spatial Domain	Spatial Resolution	Temporal Domain	Temporal Resolution	Climate Variables	Projections	GCMs	Emission Scenarios
CMIP5 MACA – Livneh v2	CONUS	$^{1}/_{16}$° by $^{1}/_{16}$°	1950-2099	Daily	Precipitation at surface [in/day]; Maximum air temperature near surface [°C] Minimum air temperature near surface [°C] Mean specific humidity near surface [-] Mean downward shortwave radiation [W/m^2] Mean wind speed near surface [m/s]	20	20	RCP 4.5 RCP 8.5
ARRM	CONUS, Alaska	$^{1}/_{8}$° by $^{1}/_{8}$° (CONUS) 1/2° by 1/2° (Alaska)	1960-2099	Daily	Precipitation at surface [in/day] Maximum air temperature near surface [°C] Minimum air temperature near surface [°C]	42	16	SRES B1 SRES A1B SRES A1FI SRES A2
NEX-GDDP	Global	$^{1}/_{4}$° by $^{1}/_{4}$°	1950-2100	Daily	Maximum air temperature near surface [°C] Minimum air temperature near surface [°C] Precipitation at surface [mm/day]	42	21	RCP 4.5 RCP 8.5
NARCCAP	CONUS	$^{1}/_{2}$° by $^{1}/_{2}$°	1971-2000; 2041-2070	3-hourly	Precipitation at surface [kg/m^2/s] Air temperature near surface [K] Eastward component of wind [m/s] Northward component of wind [m/s] Air pressure [Pa] Specific humidity [-] Downwelling shortwave radiation [W/m^2] (additional variables are provided for most models – see website)	12	4	SRES A2
USGS Dynamically Downscaled Simulations over North America	CONUS, Eastern US, Western US	15 km (Eastern and Western US) 50 km (CONUS)	1968-2099	6 Hours	Temperature Precipitation	4	4	SRES A2

Units:
°C = degrees Celcius
in/day = inches per day
K = Kelvin
kg/m^2/s= kilograms per meter squared per second, approximately equal to mm per second for liquid water
m = meter
mm = millimeter
m/s = meters per second
Pa = pascals
W/m^2 = Watts per meter squared
- = dimensionless (no units)

4.2.1. CMIP3 Bias Correction and Spatial Disaggregation (BCSD)

Spatial Domain	CONUS, plus portions of southern Canada and northern Mexico
Spatial Resolution	$^1/_8$° latitude by $^1/_8$° longitude (approximately 12 km north-south by 12 km east-west)
Temporal Domain	1950 – 2099
Temporal Resolution	Monthly
Climate Variables	Total precipitation [mm] Mean surface air temperature [°C]
Projections	112
GCMs	16
Scenarios	3 (SRES B2, A1B, A2)
URL	http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html

Background

Reclamation, in collaboration with six other Federal and non-federal collaborators, developed a suite of downscaled climate projections and corresponding hydrology projections for use in water resources planning and management (Reclamation et al. 2013). Within this suite, the CMIP3 Bias Corrected and Spatially Disaggregated (BCSD) climate projection dataset provides an ensemble of 112 bias corrected and downscaled projections of monthly total precipitation in millimeters per month [mm/month] and monthly mean surface air temperature in degrees Celsius [°C] at a downscaling target resolution of $^1/_8$° latitude by $^1/_8$° longitude (approximately 12 km by 12 km at mid-latitudes).

Methodology

The CMIP3 monthly BCSD dataset was developed by applying the BCSD downscaling methodology to an ensemble of 112 GCM-based global climate projections from the CMIP3 multi-model dataset, including projections from 16 different GCMs under three SRES emissions scenarios (B1, A1B, and A2). The BCSD methodology is a two-step quantile mapping technique applied on a monthly and location-specific basis (Maurer et al. 2007 and Reclamation et al. 2013). The first step involves removing biases from the raw GCM projections, and the second step involves spatially disaggregating the bias-corrected GCM projections to the target downscaling resolution. The BCSD procedure combines bias-corrected climate variability and trends from coarser-resolution global climate projections with long-term average climate conditions (climatology) from higher-resolution historical observations to develop a bias-corrected and spatially-disaggregated climate projection.

Bias correction is carried out by first aggregating finer-resolution historical observations of precipitation and temperature to the coarser GCM resolution. A simple quantile-mapping procedure is then applied on a monthly basis to remove biases in GCM data such that for each coarse-resolution grid cell, the cumulative distribution function (CDF) of monthly GCM values over the bias correction period matches the CDF of observed monthly values over this period.

The gridded historical precipitation and temperature dataset of Maurer et al. (2002) was used as the observational basis for bias correction of CMIP3 GCM output, with a bias correction period of 1950-1999. The spatial resolution of raw GCM output varies among models in the CMIP3 multi-model dataset; for consistency, observations and raw CMIP3 GCM output over the target downscaling region were regridded to a common spatial resolution of 2.0° latitude by 2.0° longitude prior to bias correction. For each 2.0° by 2.0° grid cell, CDFs were developed for observed and simulated precipitation and temperature. CDFs were constructed for each month of the year based on the historical reference period 1950-1999. Quantile mapping was then applied such that the CDFs of bias corrected GCM output for each month and grid cell over the period 1950-1999 matched the corresponding observed CDF. The same quantile mapping procedure was then applied to the future period 2000-2099. For the future period, the bias corrected GCM values reflect the relative changes in mean, variance, and other statistical moments between the 20th and 21st centuries as projected by the unadjusted GCM output, but mapped onto the observed variance (Reclamation et al. 2013).

It should be noted that per the recommendation of Wood et al. (2004), the linear trend in GCM temperatures over the future period was removed prior to applying bias correction. The trend was subsequently imposed onto the bias-corrected temperatures for the future period. The trend was removed to ensure that bias correction does not alter projected interannual (year-to-year) variability over the future period, and to ensure that the downscaled dataset preserves the future trends in future temperature from the global projections. As precipitation trends in global projections are generally weak, trends in future precipitation were not removed prior to bias correction.

Spatial disaggregation was carried out over the full target region for each monthly time-step by merging an historical spatial climatology with the spatially-disaggregated deviation for that time-step. An historical spatial climatology was developed for each month of the year based on the monthly mean of the observed historical climate dataset—i.e., the dataset of Maurer et al. (2002)—at both the GCM resolution and the target downscaling resolution. Deviation factors were then computed at each monthly time-step for each GCM grid cell.

Precipitation factors are computed as the ratio of the bias-corrected GCM precipitation for each month divided by the precipitation value from the historical spatial climatology for the corresponding grid cell and month; temperature factors are computed as the difference between the corrected GCM temperature and the historical spatial climatology. Deviation factors were interpolated to the downscaling target resolution ($^1/_8$° latitude by $^1/_8$° longitude), and then applied to the historical spatial climatology at the downscaling target resolution.

Usage Notes

The BCSD methodology is conceptually simple and computationally efficient, thus making it easy to implement over relatively large areas and for a large number of GCM projections. Recent analysis and comparison of downscaling techniques by Gutmann et al. (2014) also demonstrates that the BCSD methodology introduces few biases with respect to projected changes precipitation and temperature from the raw GCM results compared to other comparable statistical downscaling methods when considered at the monthly timescale. However, if daily data are required, temporal disaggregation from monthly to daily values based on observed historical weather sequences does not allow for changes in the frequency and duration of weather events. As a result, the BCSD method does not account for projected changes in the frequency, duration, and intensity of precipitation events. In addition, for this dataset, the BCSD methodology preserves GCM-projected trends in projected temperature, but not in projected precipitation (see above). This results in slight differences between projected precipitation trends between the BCSD CMIP3 dataset and the corresponding GCM projections.

Similar to all statistical downscaling approaches, the BCSD method exhibits two important limitations. First, the stationarity assumption inherent in all statistical downscaling methods limits the ability to represent projected changes in spatial patterns of weather and climate variability (see Section 2.2.3.). Second, the reliance of statistical downscaling methods on high-quality, high-resolution observations of historical climate conditions is likely to result in errors over areas with widespread sparse measurements, extensive irrigated agriculture, and/or complex topography.

4.2.2. CMIP5 Bias Correction and Spatial Disaggregation (BCSD)

Spatial Domain	CONUS, plus portions of southern Canada and northern Mexico
Spatial Resolution	$^1/_8$° latitude by $^1/_8$° longitude (approximately 12 km north-south by 12 km east-west)
Temporal Domain	1950 – 2099
Temporal Resolution	Monthly
Climate Variables	Total precipitation [mm] Mean surface air temperature [°C] Maximum surface air temperature [°C] Minimum surface air temperature [°C]
Projections	234
GCMs	37
Scenarios	4 (RCPs 2.6, 4.5, 6.0, and 8.5)
URL	http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/ dcpInterface.html

Background

Reclamation, in collaboration with six Federal and non-federal collaborators, developed a suite of downscaled climate projections and corresponding hydrology projections for use in water resources planning and management (Reclamation et al. 2013). Within this suite, the CMIP5 monthly BCSD climate projection dataset provides an ensemble of 234 bias corrected and downscaled projections of monthly total precipitation [mm/month] and monthly mean, maximum, and minimum surface air temperature [°C] at a downscaling target resolution of $^1/_8$° latitude by $^1/_8$° longitude (approximately 12 km by 12 km at mid-latitudes).

Methodology and Usage Notes

The CMIP5 BCSD dataset was developed using the same procedure as the CMIP3 BCSD dataset (see Section 4.2.1. for a summary of the BCSD methodology and usage notes).

4.2.3. CMIP3 Bias-Correction and Constructed Analogue (BCCA)

Spatial Domain	CONUS, plus portions of southern Canada and northern Mexico
Spatial Resolution	$^{1}/_{8}$° latitude by $^{1}/_{8}$° longitude (approximately 12 km north-south by 12 km east-west)
Temporal Domain	1961-2000; 2046-2065; 2081-2100
Temporal Resolution	Daily
Climate Variables	Total precipitation [mm] Maximum surface air temperature [°C] Minimum surface air temperature [°C]
Projections	53
GCMs	9
Scenarios	3 (SRES B2, A1B, and A2)
URL	http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/ dcpInterface.html

Background

Reclamation, in collaboration with six Federal and non-federal collaborators, developed a suite of downscaled climate projections and corresponding hydrology projections for use in water resources planning and management (Reclamation et al. 2013). Within this suite, the CMIP3 Bias Corrected Constructed Analogues (BCCA) (version 2) dataset provides an ensemble of 53 bias corrected and downscaled projections of daily total precipitation [mm/day] and daily maximum and minimum surface air temperature [°C] at a downscaling target resolution of $^{1}/_{8}$° latitude by $^{1}/_{8}$° longitude (approximately 12 km by 12 km at mid-latitudes).

Methodology

The CMIP3 daily BCCA dataset was developed by applying the BCCA downscaling methodology to an ensemble of 53 GCM-based global climate projections from the CMIP3 multi-model dataset, including projections from nine different GCMs under three emissions scenarios (SRES B1, A1B, and A2). The number of GCM projects and the time periods included in the CMIP3 BCCA dataset were limited by the availability of daily GCM output in CMIP3 multi-model dataset.

The BCCA methodology is a two-step technique applied on a daily basis. Similar to the monthly BCSD methodology, the first step in the BCCA procedure involves applying a simple quantile mapping technique to remove biases from the GCM projections at each GCM grid cell. The second step involves downscaling the bias-corrected GCM projections to the target resolution of $^{1}/_{8}$° latitude by $^{1}/_{8}$° longitude using a constructed analogue approach (Hidalgo et al. 2008 and Reclamation et al. 2013).

Bias correction was carried out by first aggregating historical observations of precipitation and temperature to the GCM resolution, and then applying a simple quantile-mapping procedure to remove biases in GCM data such that the cumulative distribution function (CDF) of daily GCM values matches the CDF of observed values. For the BCCA methodology, bias correction was applied at a daily timestep relative to Julian date, with CDFs developed for each day of the year based on daily precipitation and temperature values pooled over a 31-day window centered on that day (Reclamation 2013). For example, the CDF for March 1 was developed based on daily values over the window from February 14 through March 16. The gridded historical precipitation and temperature dataset of Maurer et al. (2002) was used as the observational basis for bias correction of CMIP3 GCM output.

For consistency with the limited availability of daily output from CMIP3, bias correction was based on observations over the period 1961-1999. The spatial resolution of raw GCM output varies among models in the CMIP3 multi-model dataset; for consistency, observations and raw CMIP3 GCM output were regridded to a common spatial resolution of 2.0° latitude by 2.0° longitude prior to bias correction. For each 2.0° by 2.0° grid cell over the target downscaling region, CDFs were developed for each day of the year for observed and simulated daily precipitation and temperature. Quantile mapping was then applied such that the CDFs of GCM output for each day and grid cell matched the corresponding observed CDF.

It should be noted that the linear trend in GCM temperatures over the future period was removed prior to applying bias correction, similar to the CMIP3 and CMIP5 BCSD datasets (Sections 4.2.1. and 4.2.2.), per the recommendation of Wood et al. (2004). The trend was subsequently imposed onto the bias-corrected temperatures for the future period. The trend was removed to ensure that bias correction does not alter projected interannual variability over the future period, and to ensure that the downscaled dataset preserves the future trends in future temperature from the global projections. As precipitation trends in global projections are generally weak, trends in future precipitation were not removed prior to bias correction.

Spatial downscaling was then carried out using a constructed analogues approach (Hidalgo et al. 2008 and Reclamation et al. 2013). The constructed analogues approach involves identifying a set of observed daily climate patterns at the GCM resolution such that a weighted linear combination of observed daily patterns closely approximates the bias corrected GCM pattern. For any given day in the GCM record, downscaling is achieved based on the corresponding weighted linear combination of observed daily conditions at the target downscaling resolution. For example, the bias corrected GCM precipitation pattern for March 1 is used to identify a set of observed coarse-resolution daily precipitation patterns that most closely resemble the March 1 GCM precipitation pattern, where similarity between observed and GCM precipitation patterns is based on the spatial root mean square error (Hidalgo et al. 2008). A set of weights (one for each of the selected observed daily precipitation patterns) is then computed via regression such that the weighted (linear) sum of observed daily precipitation patterns approximates the March 1 GCM precipitation pattern. Finally, the downscaled GCM precipitation pattern is computed as the weighted sum of the selected observed precipitation patterns at the target downscaling resolution.

In implementing the constructed analogues approach, a set of 30 observed patterns were selected to construct each daily analogue. For each daily GCM pattern, 30 observed patterns were selected from a 91-day seasonal window encompassing the date of the target GCM pattern plus 45 days before and after that date. Analogues were constructed based on climate anomaly patterns, where anomalies were calculated as the difference between the pattern on the target date and the mean pattern over the period 1961-1999. Analogue construction was coordinated for daily maximum and minimum temperatures and carried out independently for precipitation. Lastly, it should be noted that precipitation was transformed to the square root of precipitation before constructing anomalies and analogues to reduce potential biases associated with the heavily skewed distribution of daily precipitation over many regions.

Usage Notes

Similar to other statistical downscaling methods, the BCCA methodology is relatively computationally efficient and, therefore, readily applied to large areas and large numbers of GCM projections. However, recent analyses have demonstrated that the BCCA methodology exhibits significant dry biases, particularly when applied to large regions such as the CONUS (e.g., Gutmann et al. 2014). As suggested by Gutmann et al. (2014), "*BCCA is likely to select analogue days with smoother spatial patterns, resulting in a decrease of larger precipitation events . . . and these larger events will affect mean annual totals substantially*." Conversely, BCCA also exhibits a higher wet-day fraction (fraction of days exhibiting precipitation) than observed (Gutmann et al. 2014). Both of these artifacts have the potential to significantly bias subsequent analyses of hydrology and water resources under climate change. In addition, for this dataset, the BCCA methodology preserves GCM-projected trends in projected temperature, but not in projected precipitation (see above). This results in slight differences between projected precipitation trends between the BCCA CMIP3 dataset and the corresponding GCM projections.

Similar to all statistical downscaling approaches, the BCCA method exhibits two important limitations. First, the stationarity assumption inherent in all statistical downscaling methods limits the ability to represent projected changes in spatial patterns of weather and climate variability (see Section 2.2.3.). Second, the reliance of statistical downscaling methods on high-quality, high-resolution observations of historical climate conditions is likely to result in errors over areas with widespread sparse measurements, extensive irrigated agriculture, and/or complex topography.

4.2.4. CMIP5 Bias-Correction and Constructed Analogue (BCCA)

Spatial Domain	CONUS, plus portions of southern Canada and northern Mexico
Spatial Resolution	$^1/_8$° latitude by $^1/_8$° longitude (approximately 12 km north-south by 12 km east-west)
Temporal Domain	1950-2099
Temporal Resolution	Daily
Climate Variables	Total precipitation [mm] Maximum surface air temperature [°C] Minimum surface air temperature [°C]
Projections	134
GCMs	20
Scenarios	4 (RCPs 2.6, 4.5, 6.0, and 8.5)
URL	http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html

Background

Reclamation, in collaboration with six Federal and non-federal collaborators, developed a suite of downscaled climate projections and corresponding hydrology projections for use in water resources planning and management (Reclamation et al. 2013). Within this suite, the CMIP5 BCCA (version 2) dataset provides an ensemble of 134 bias corrected and downscaled projections of daily total precipitation [mm/day] and daily maximum and minimum surface air temperature [°C] at a downscaling target resolution of $^1/_8$° latitude by $^1/_8$° longitude (approximately 12 km by 12 km at mid-latitudes).

Methodology

The CMIP5 BCCA dataset was developed using the same procedure as the CMIP3 BCCA dataset, described in Section 4.2.3, with two exceptions. First, the historical period used in the bias correction step for the CMIP5 BCCA dataset is 1950-1999, whereas the historical period used for the CMIP3 dataset is 1961-1999. The shorter period was used for the CMIP3 dataset due to the limited availability of daily GCM output in the CMIP3 multi-model dataset. Second, downscaled daily maximum and minimum temperature fields for the CMIP5 dataset were constructed by applying the bias correction and constructed analogue steps to daily maximum temperature and daily diurnal temperature range (DTR, calculated as the difference between daily maximum and minimum temperatures). Daily minimum temperature was subsequently calculated by subtracting the BCCA DTR from the BCCA daily maximum temperature. By contrast, the bias correction and constructed analogue steps were applied directly to daily maximum and minimum temperatures for the CMIP3 BCCA dataset.

Usage Notes

The CMIP5 BCCA dataset was developed using the same overall procedure as the CMIP3 BCCA dataset; refer to Section 4.2.3. for general BCCA usage notes.

In addition to the usage notes provided in Section 4.2.3, application of the BCCA method to daily maximum temperature and DTR in the CMIP5 dataset—rather than to daily maximum and minimum temperatures as in the CMIP3 dataset—addresses the occasional occurrence of downscaled minimum temperature exceeding downscaled maximum temperature. When this occurred in the CMIP3 dataset, the values were simply switched so that the maximum temperature would be the greater of the two temperature values. See Reclamation et al. 2013 for details.

4.2.5. CMIP5 Multivariate Adaptive Constructed Analogue (MACA) – METDATA v1

Spatial Domain	Western United States (31.02°-49.1°N, 124.77°-103.02°W)
Spatial Resolution	$^{1}/_{24}$° latitude by $^{1}/_{24}$° longitude (approximately 4 km north-south by 4 km east-west)
Temporal Domain	1950-2100
Temporal Resolution	Daily
Climate Variables	Precipitation at surface [kg/m^2/s] Maximum air temperature near surface [°C] Minimum air temperature near surface [°C] Maximum relative humidity near surface [-] Minimum relative humidity near surface [-] Mean specific humidity near surface [-] Mean downward shortwave radiation at surface [W/m^2] Mean wind speed near surface [m/s] Mean eastward component of wind near surface [m/s] Mean eastward component of wind near surface [m/s]
Projections	20
GCMs	20
Scenarios	2 (RCPs 4.5 and 8.5)
URL	http://maca.northwestknowledge.net/index.php

Background

The Multivariate Adaptive Constructed Analogues (MACA) method is a statistical method for downscaling daily GCM outputs of multiple climate variables from their coarse native resolution to a finer spatial resolution that is applicable to impact modeling, including analysis of climate change impacts on water and environmental resources at regional and local scales. There are three MACA datasets available: MACA METDATA v1, MACA METDATA v2, and MACA Livneh v2. The different MACA datasets use different observational datasets in the statistical downscaling procedure. The different datasets also encompass different spatial domains and exhibit minor differences in implementing the MACA method.

Methodology

The MACA METDATA v1 dataset was developed by applying the MACA method to daily outputs from 20 GCM projections in the CMIP5 multi-model dataset over the Western United States using the University of Idaho Gridded Surface Meteorology Dataset (METDATA). The MACA METDATA v1 dataset was developed and made available to the public through a collaborative effort by the University of Idaho, Climate Impacts Research Consortium (CIRC), Northwest Knowledge Network (NKN), Regional Approaches to Climate Change – Pacific Northwest Agriculture (REACCH), Northwest Climate Science Center, and Southeast Climate Science Center (see maca.northwestknowledge.net for details).

The MACA METDATA v1 dataset was developed by applying the MACA method to daily outputs from 20 GCM projections in CMIP5 multi-model dataset to provide downscaled projections of daily precipitation, maximum and minimum air temperature, maximum and minimum relative humidity, mean specific humidity, mean downward shortwave radiation, and wind speed over the Western United States (31.02°-49.1°N, 124.77°-103.02°W). The MACA method is designed to downscale GCM outputs to finer spatial resolutions that *"captures both the scales relevant for impact modeling while preserving time-scales and patterns of meteorology simulated by GCMs"* (MACA 2015).

The MACA method requires daily observations of all variables to be downscaled at the target downscaling resolution, along with daily GCM outputs for all variables. The MACA method is then implemented as a series of six steps, summarized below; complete details of the method are provided by Abatzoglou and Brown (2011).

Step 1: Regrid to Common Coarse Resolution
Regrid observations and GCM outputs to a common coarse-resolution grid. For the MACA METDATA v1 dataset, a coarse-resolution grid of 1.0° latitude by 1.0° longitude was used.

Step 2: Remove Trends (Epoch Adjustment)
Remove seasonal and annual trends at each grid point. For the MACA METDATA v1 dataset, trends are calculated using a 21-day and 31-year mean at each coarse-resolution grid cell.

Step 3: **Coarse Resolution Bias Correction**
Bias correct cumulative distribution functions (CDFs) of coarse-resolution GCM outputs for each variable using the Equidistant Quantile Mapping (EDCDFm) method of Li et al. (2010). CDFs are developed for each grid cell and for each day of the year based on all years of data (historical and future) using a 15-day window around the target day. The EDCDFm method adjusts the historical GCM CDF to match the observed CDF, then adjusts the future GCM CDF to preserve differences between historical and future GCM CDFs. As implemented in the MACA method, the bias correction preserves additive future differences for temperature and relative differences in precipitation (i.e., ratio of future to historical precipitation).

Step 4: Constructed Analogues
The constructed analogues approach involves identifying a set of coarse-resolution observed daily climate patterns such that a weighted linear combination of observed daily patterns closely approximates the bias corrected coarse-resolution GCM pattern. For any given day in the GCM record, downscaling is achieved based on the corresponding weighted linear combination of observed daily conditions at the target downscaling resolution. For example, the bias corrected GCM precipitation pattern for March 1 is used to identify a set of observed coarse-resolution daily precipitation patterns that most closely resemble the March 1 GCM precipitation pattern, where similarity between observed and GCM precipitation patterns is based on the spatial root mean square error (Hidalgo et al. 2008). A set of weights (one for each of the selected observed daily precipitation patterns)

is then computed via matrix inversion such that the weighted (linear) sum of observed daily precipitation patterns approximates the March 1 GCM precipitation pattern. Finally, the downscaled GCM precipitation pattern is computed as the weighted sum of the selected observed precipitation patterns at the target downscaling resolution. Implementation of the constructed analogues approach in the MACA method uses a set of 100 observed patterns to construct each daily analogue. For each daily GCM pattern, 100 observed patterns were selected from a 91-day seasonal window encompassing the date of the target GCM pattern plus 45 days before and after that date.

Step 5: Replace Trends (Epoch Replacement)
For each variable for which trends were removed in Step 2, trends are replaced to ensure consistency with GCM data.

Step 6: Fine Bias Correction
Bias correct CDFs of downscaled GCM outputs (i.e., constructed analogues) using the same procedure as Step 3, but applied using fine-resolution observations and GCM outputs.

Usage Notes
MACA downscaled climate projections have been used in recent climate change impact analyses, including analyses of climate change impacts on water and environmental resources in the Western United States. Similar to other statistical downscaling methods, the MACA method is relatively computationally efficient and therefore readily applied to large areas and large numbers of GCM projections.

The MACA method has also been shown to compare well to other daily downscaling methods and to be preferable over daily downscaling methods that require direct interpolation of meteorological fields (Abatzoglou and Brown 2011). In addition, the MACA method avoids the assumption of stationarity in daily weather patterns that is inherent in some downscaling methods that rely on resampling of historical daily weather patterns to obtain downscaled daily climate projections. The method also provides downscaled projections of future humidity and winds, which strongly affect evapotranspiration (ET) and thus agricultural water demands.

However, similar to the BCCA method, the MACA method is sensitive to the spatial extent of the chosen domain, with potential biases occurring when applied over large domains such as the CONUS, particularly for precipitation (Fowler et al. 2007, Abatzoglou and Brown 2011, and Gutmann et al. 2014). The method also assumes that GCMs are capable of simulating realistic synoptic weather patterns, and that the relationship between coarse-resolution and finer-resolution weather patterns remains constant under future climate conditions (Abatzoglou and Brown 2011). Finally, as with other statistical downscaling methods, the MACA methodology relies on the availability of high-quality, high-resolution gridded observations. Errors and uncertainties in gridded observations result in corresponding errors in downscaled projections, particularly over areas with few gages and complex topography.

4.2.6. CMIP5 Multivariate Adaptive Constructed Analogue (MACA) – METDATA v2

Spatial Domain	CONUS
Spatial Resolution	$^{1}/_{24}$° latitude by $^{1}/_{24}$° longitude (approximately 4 km north-south by 4 km east-west)
Temporal Domain	1950-2099
Temporal Resolution	Daily
Climate Variables	Precipitation at surface [kg/m^2/s] Maximum air temperature near surface [°C] Minimum air temperature near surface [°C] Maximum relative humidity near surface [-] Minimum relative humidity near surface [-] Mean specific humidity near surface [-] Mean downward shortwave radiation at surface [W/m^2] Mean wind speed near surface [m/s] Mean eastward component of wind near surface [m/s] Mean eastward component of wind near surface [m/s]
Projections	20
GCMs	20
Scenarios	2 (RCPs 4.5 and 8.5)
URL	http://maca.northwestknowledge.net/index.php

Background

The MACA method is a statistical method for downscaling daily GCM outputs of multiple climate variables from their coarse native resolution to a finer spatial resolution that is applicable to impact modeling, including analysis of climate change impacts on water and environmental resources at regional and local scales. There are three MACA datasets available: MACA METDATA v1, MACA METDATA v2, and MACA Livneh v2. The different MACA datasets use different observational datasets in the statistical downscaling procedure. The different datasets also encompass different spatial domains and exhibit minor differences in implementing the MACA method.

Methodology

The MACA METDATA v2 dataset was developed by applying the MACA method to daily outputs from 20 GCM projections in the CMIP5 multi-model dataset over the CONUS using the University of Idaho Gridded Surface Meteorology Dataset (METDATA). The MACA METDATA v2 dataset was developed and made available to the public through a collaborative effort by the University of Idaho, Climate Impacts Research Consortium (CIRC), Northwest Knowledge Network (NKN), Regional Approaches to Climate Change – Pacific Northwest Agriculture (REACCH), Northwest Climate Science Center, and Southeast Climate Science Center (see maca.northwestknowledge.net for details).

The MACA METDATA v2 dataset was developed using the same procedure as the MACA METDATA v1 dataset, described in Section 3.2.5, with the following exceptions listed below. For additional details, refer to the MACA website: http://maca.northwestknowledge.net/MACAmethod.php.

- The MACA method was applied over the entire CONUS in the v2 dataset, compared to the Western United States in the v1 dataset.
- Trend removal (Step 2) was applied to all variables in the v2 dataset, compared to temperature and wind variables in the v1 dataset.
- Trend removal (Step 2) was applied to both the historical and future GCM outputs in the v2 dataset, compared to just the future GCM outputs in the v1 dataset.
- Trend removal was applied a second time following coarse resolution bias correction (Step 3) of multiplicative variables (precipitation, specific humidity, and wind speed) in the v2 dataset as coarse resolution bias correction may affect trends; secondary trend removal was not applied in the v1 dataset.
- Constructed analogues (Step 4) were developed from the 10 most similar observed spatial patterns in the v2 dataset, compared to the 100 most similar observed patterns in the v1 dataset.
- The error in the coarse-resolution constructed analogue was interpolated to the finer-resolution grid and added to the finer-resolution constructed analogue in the v2 dataset. By contrast, the error in coarse-resolution constructed analogues was not included in the v1 dataset.
- Finer resolution bias correction (Step 6) of maximum and minimum air temperatures was carried out jointly with precipitation in the v2 dataset; finer resolution bias correction was carried out independently for all variables in the v1 dataset.

Usage Notes

See usage notes for MACA METDATA v1 dataset in Section 4.2.5.

4.2.7. CMIP5 Multivariate Adaptive Constructed Analogue (MACA) – Livneh v2

Spatial Domain	CONUS, plus Columbia River Basin in Canada
Spatial Resolution	$^{1}/_{16}$° latitude by $^{1}/_{16}$° longitude (approximately 6 km north-south by 6 km east-west)
Temporal Domain	1950-2099
Temporal Resolution	Daily
Climate Variables	Precipitation at surface [in/day] Maximum air temperature near surface [°C] Minimum air temperature near surface [°C] Mean specific humidity near surface [-] Mean downward shortwave radiation at surface [W/m^2] Mean wind speed near surface [m/s]
Projections	20
GCMs	20
Scenarios	2 (RCPs 4.5 and 8.5)
URL	http://maca.northwestknowledge.net/index.php

Background
The MACA method is a statistical method for downscaling daily GCM outputs of multiple climate variables from their coarse native resolution to a finer spatial resolution that is applicable to impact modeling, including analysis of climate change impacts on water and environmental resources at regional and local scales. There are three MACA datasets available: MACA METDATA v1, MACA METDATA v2, and MACA Livneh v2. The different MACA datasets use different observational datasets in the statistical downscaling procedure. The different datasets also encompass different spatial domains and exhibit minor differences in implementing the MACA method.

Methodology
The MACA Livneh v2 dataset was developed using the same procedure as the MACA METDATA v2 dataset, described in Section 4.2.6.

The MACA Livneh v2 dataset was developed by applying the MACA method to daily outputs from 20 GCM projections in the CMIP5 multi-model dataset over the CONUS, plus the portion of the Columbia River Basin in Canada, using the gridded daily meteorology dataset of Livneh et al. (2013). The MACA Livneh v2 dataset was developed and made available to the public through a collaborative effort by the University of Idaho, Climate Impacts Research Consortium (CIRC), Northwest Knowledge Network (NKN), Regional Approaches to Climate Change – Pacific Northwest Agriculture (REACCH), Northwest Climate Science Center, and Southeast Climate Science Center (see maca.northwestknowledge.net for details).

Usage Notes
See usage notes for MACA METDATA v1 dataset in Section 3.2.5.

4.2.8. Asynchronous Regional Regression Model (ARRM)

Spatial Domain	CONUS, plus southern Canada, northern Mexico, and Alaska
Spatial Resolution	$^{1}/_{8}$° latitude by $^{1}/_{8}$° longitude over CONUS, S. Canada, N. Mexico (approximately 12 km north-south by 12 km east-west) $^{1}/_{2}$° latitude by $^{1}/_{2}$° longitude over Alaska (approximately 50 km north-south by 35 km east-west)
Temporal Domain	1960-2099
Temporal Resolution	Daily
Climate Variables	Precipitation at surface [in/day] Maximum air temperature near surface [°C] Minimum air temperature near surface [°C]
Projections	42
GCMs	16
Scenarios	4 (SRES B1, A1B, A1FI, A2)
URL	http://cida.usgs.gov/thredds/catalog.html?dataset=cida.usgs.gov/thredds/dcp/conus_pr

Background

The Asynchronous Regional Regression Model (ARRM) is a statistical downscaling model that defines quantitative relationships between daily observed and simulated surface variables, with a particular emphasis on capturing simulated changes in extremes (Stoner et al. 2012). The ARRM downscaled climate projection dataset was developed by applying the ARRM method to downscale projected daily precipitation and daily maximum and minimum temperatures from 16 different GCMs and 4 future emissions scenarios from the CMIP3 multi-model dataset. Downscaled projections cover the CONUS, southern Canada, and northern Mexico at a downscaling target resolution of $^{1}/_{8}$° latitude by $^{1}/_{8}$° longitude (approximately 12 km by 12 km at mid-latitudes) and Alaska at a downscaling target resolution of $^{1}/_{2}$° latitude by $^{1}/_{2}$° longitude (approximately 35 km by 20 km over central Alaska).

Methodology

Regression-based methods are based on developing quantitative relationships between variables based on their covariance, where covariance is a statistical measure of the extent to which two variables vary together. In most climate and hydrology applications, regression-based methods are used to represent the temporal variability of one variable with that of another (e.g., a regression model may be used to estimate precipitation at one location based on precipitation at another nearby location or locations). By contrast, ARRM is an extension of the quantile regression method (Koenker and Basset 1978), which estimates relationship between the quantiles[18] of two datasets rather than between the temporal variability of the datasets (i.e., the relationship between the quantiles of one variable and those of another variable). As summarized by Stoner et al. (2012):

[18] Quantiles are values taken at regular intervals from the inverse function of the cumulative distribution function (CDF) of a random variable such that the population of the random variable is divided into equal-size segments (Stoner et al. 2012).

> *"A model can be constructed by regressing the value at rank n_i of the simulated vector onto the value of the same rank of the vector containing observed values, for i=1 [to] N . . . This regression is asynchronous, i.e., data values that are regressed against each other did not necessarily occur the same calendar day, but rather correspond by quantile or rank. The regression model derived from historical [GCM] simulations and historical observations can then be applied to future [GCM] simulations, to project downscaled future conditions."*

To account for non-linearity in the relationship between observed and simulated climate conditions, ARRM uses a piece-wise approach to develop regression relationships between GCM outputs (predictor) and historical observations (predictand). To avoid unrealistically large or small extreme values, quality control measures are applied to the observational dataset prior to applying the ARRM methodology. The magnitude of ARRM outputs (i.e., downscaled climate variables) is also constrained to avoid spurious results that can arise due to the limited number of data points in the tails of the distribution and the sensitivity of regression slopes to individual outliers in the tails (Stoner et al. 2012).

The ARRM downscaling dataset was developed based on the gridded observational dataset of Maurer et al. (2002). Piece-wise quantile regression relationships developed using observed and simulated data over the period 1960-1999. These relationships were then used to downscale historical and future GCM output for the period 1960-2099. The resulting dataset provides daily downscaled precipitation, maximum air temperature, and minimum air temperature for the period 1960-2099 at $^1/_8$° resolution over the CONUS, southern Canada, and northern Mexico and at $^1/_2$° resolution over Alaska.

Usage Notes

The ARRM methodology is conceptually simple and computationally efficient, thus making it easy to implement over relatively large areas and for a large number of GCM projections. The piece-wise approach to developing regression relationships used by ARRM improves downscaling of extreme events over the historical climate period (see Stoner et al. 2012). However, the ARRM method may alter projected trends in temperature and precipitation—i.e., trends in ARRM downscaled projections may differ from trends in the corresponding raw GCM projection prior to downscaling. The overall advantages of the ARRM method for downscaling projected climate conditions compared to other statistical downscaling methods are not well understood at this time.

Similar to all statistical downscaling approaches, the ARRM method exhibits two important limitations. First, the stationarity assumption inherent in all statistical downscaling methods (see Section 2.2.3.) limits the ability to represent projected changes in weather and climate variability. Second, the reliance of statistical downscaling methods on high-quality, high-resolution observations of historical climate conditions is likely to result in errors over areas with widespread sparse measurements, extensive irrigated agriculture, and/or complex topography.

4.2.9. NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP)

Spatial Domain	Global
Spatial Resolution	$^{1}/_{4}$° latitude by $^{1}/_{4}$° longitude (approximately 25 km north-south by 25 km east-west)
Temporal Domain	1950-2100
Temporal Resolution	Daily
Climate Variables	Precipitation at surface [in/day] Maximum air temperature near surface [°C] Minimum air temperature near surface [°C]
Projections	42
GCMs	21
Scenarios	2 (RCP 4.5 and 8.5)
URL	https://cds.nccs.nasa.gov/nex-gddp/

Background

The National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) contains statistically downscaled climate projections from CMIP5 multi-model archive. NEX-GDDP includes downscaled projections under RCP 4.5 and RCP 8.5 from the 21 models for which daily scenarios were produced and distributed under CMIP5. Each climate projection includes daily maximum and minimum temperature and daily precipitation for the period between 1950-2100. The target downscaling domain encompasses global and areas at a target downscaling resolution of $^{1}/_{4}$° latitude by $^{1}/_{4}$° longitude (approximately 24 km by 24 km at mid-latitudes).

Methodology

The NEX-GDDP dataset is based on the BCSD downscaling method (see Section 4.2.1. for a summary of the BCSD method). Rather than being applied at a monthly timescale as described in Section 4.2.1, however, NEX-GDDP is based on application of the BCSD method at a daily timescale. Similar to the bias correction portion of the BCCA method (Section 4.2.3.), BCSD was applied on a for each Julian day by pooling daily temperature and precipitation values over a 31-day window (target day plus 15 days prior and after). Otherwise, the BCSD method is applied as described in Section 4.2.1.

NEX-GDDP applied the BCSD method using gridded historical precipitation and temperature data from the Global Meteorological Forcing Dataset (GMFD) for Land Surface Modeling developed by the Terrestrial Hydrology Research Group at Princeton University (Sheffield et al. 2006). The dataset is available at a spatial resolution of 0.25°, 0.5°, and 1.0°. The temporal resolution is available at 3-hour, daily, and monthly timesteps. The NEX-GDDP dataset used the 0.25° historical data for the climate variables for the period 1950-2005.

Usage Notes

The NEX-GDDP dataset is based on the BCSD downscaling method (see Section 4.2.1. for usage notes).

4.2.10. NASA Earth Exchange Downscaled 30 Arc-Second CMIP5 Climate Projections (NEX-DCP30)

Spatial Domain	CONUS, plus portions of southern Canada and northern Mexico
Spatial Resolution	30 arcseconds latitude by 30 arcseconds longitude (approximately 800 m north-south by 800 m east-west)
Temporal Domain	1950-2100
Temporal Resolution	Monthly
Climate Variables	Precipitation at surface [in/day] Maximum air temperature near surface [°C] Minimum air temperature near surface [°C]
Projections	42
GCMs	21
Scenarios	2 (RCP 4.5 and 8.5)
URL	https://cds.nccs.nasa.gov/nex-gddp/

Background
The National Aeronautics and Space Administration (NASA) Earth Exchange Downscaled 30 Arc-Second Climate Projections (NEX-DCP30) dataset contains statistically downscaled climate projections from CMIP5 multi-model archive. NEX-GDDP includes downscaled projections under RCP 4.5 and RCP 8.5 from the 34 models for which daily scenarios were produced and distributed under CMIP5. Each climate projection includes daily maximum and minimum temperature and daily precipitation for the period between 1950-2100. The target downscaling domain encompasses global and areas at a target downscaling resolution of 30 arcseconds (0.008333°) latitude by 30 arcseconds (0.008333°) longitude (approximately 800 meters [m] by 800 m at mid-latitudes).

Methodology
The NEX-DCP30 dataset is based on the BCSD downscaling method; refer to Section 4.2.1 for a summary of the BCSD method.

NEX-DCP30 applied the BCSD method using gridded historical precipitation and temperature data from the Parameter-Elevation Relationships on Independent Slopes Model (PRISM) historical climate dataset (Daly et al. 1994).

Usage Notes
The NEX-DCP30 dataset is based on the BCSD downscaling method; refer to Section 4.2.1 for usage notes.

4.2.11. North American Regional Climate Change Assessment Program (NARCCAP)

Spatial Domain	CONUS, plus southern and central Canada, northern Mexico
Spatial Resolution	50 km by 50 km
Temporal Domain	1971-2000, 2041-2070
Temporal Resolution	3-hourly
Climate Variables	Precipitation at surface [kg/m^2/s] Air temperature near surface [K] Zonal surface wind speed [m/s] Meridional surface wind speed [m/s] Surface air pressure [Pa] Surface specific humidity [-] Surface downwelling shortwave radiation [W/m^2] (additional variables are provided for most models – see website)
Projections	12
GCMs	4
Scenarios	1 (SRES A2)
URL	http://www.narccap.ucar.edu/index.html

Background

The North American Regional Climate Change Assessment Program (NARCCAP) is an international program initiated in 2006 to develop and serve high-resolution dynamically-downscaled climate change simulations to support analysis of uncertainties in regional-scale climate projections and for use in climate change impacts research (NARRCAP 2015). The primary component of the NARCCAP dataset is based on six regional climate models (RCM) and four global climate models (GCM). Each RCM was used to dynamically downscale outputs from two GCMs under the SRES A2 emissions scenario for two 30-year periods (1971-2000 and 2041-2070) for a total of 12 dynamically downscaled climate projections. Dynamically downscaled RCM outputs encompass the majority of North America, including the CONUS, southern and central Canada, and northern Mexico, at a spatial resolution of 50 km by 50 km (Mearns et al. 2009).

Methodology

As summarized in Section 2.2.3., dynamically downscaling is carried out by nesting RCMs within GCMs (i.e., outputs from global simulations with a GCM are used as boundary conditions for a limited-area RCM over the target region). The RCM then simulates climate conditions within the target region at finer resolution based on the GCM-simulated large-scale climate conditions. The RCM thus downscales the GCM-based climate projection by simulating the physical processes that govern regional climate dynamics, similar to GCMs but over a limited area and at finer spatial resolution. In addition to their finer resolution, RCMs typically include more detailed representations of meso-scale atmospheric processes, land cover, topography, and other factors that affect local and regional weather and climate. RCMs incorporate the same atmospheric composition—including greenhouse gas and aerosol composition—as the driving GCM.

Usage Notes

Pairings of RCMs and GCMs in the NARCCAP dataset are illustrated in Table 5. A tutorial on how to use this dataset is provided on the NARCCAP website (http://www.narccap.ucar.edu/users/data-tutorial.html). Additional details of the GCMs and RCMs involved in the NARCCAP project are beyond the scope of this document.

Table 5. Pairings of RCMs and GCMs in the NARCCAP

		GCMs			
		GFDL[7]	**HADCM3**[8]	**CGCM3**[9]	**CCSM**[10]
RCMs	**ECPC**[1]	X	X		
	HRM3[2]	X	X		
	MM5[3]		X		X
	RCM3[4]	X		X	
	CRCM[5]			X	X
	WRF[6]			X	X

[1] Experimental Climate Prediction Center Regional Spectral Model
[2] Met Office Hadley Centre's Hadley Regional Climate Model
[3] Pennsylvania State University Mesoscale Model 5
[4] Abdus Salam International Center for Theoretical Physics Regional Climate Model Version 3
[5] Canadian Regional Climate Model
[6] Weather Research and Forecasting Model
[7] Geophysical Fluid Dynamics Laboratory Global Climate Model
[8] Hadley Center Coupled Model Version 3
[9] Coupled Global Climate Model Version 3
[10] Community Climate System Model

4.2.12. USGS Dynamically Downscaled Climate Simulations over North America

Spatial Domain	North America (50 km by 50 km); Eastern North America and Western North America (15km by 15km)
Spatial Resolution	50 km by 50 km (North America) 15 km by 15 km (Eastern and Western North America)
Temporal Domain	1968-2099
Temporal Resolution	6-hourly
Climate Variables	Precipitation at surface [kg/m^2/s] Air temperature near surface [K] Zonal surface wind speed [m/s] Meridional surface wind speed [m/s] Surface air pressure [Pa] Surface specific humidity [-] Surface downwelling shortwave radiation [W/m^2] (additional variables are provided for most models – see website)
Projections	12
GCMs	4
Scenarios	1 (SRES A2)
URL	http://www.narccap.ucar.edu/index.html (documentation) https://catalog.data.gov/dataset/usgs-dynamical-downscaled-regional-climate (data access)

Background
The U.S. Geological Survey (USGS) Dynamically Downscaled Climate Simulations Over North America dataset provides high-resolution climate simulations over North America by dynamically downscaling global climate projections using the RegCM3 regional climate model. The goals of the project were to assess the feasibility of developing high resolution simulations for North America, to develop high resolution weather and climate data across the temporal domain, and to develop a process for processing, summarizing, and distributing climate datasets to all potential users. Dynamically downscaled climate projections are provided for multiple models and time periods for multiple regions of interest spanning North America. Projections are provided at high spatial and temporal resolutions.

Methodology
Dynamical downscaling was performed using output from four GCMs. RegCM3 was used to downscale climate projections from three GCMs over six regional domains to capture more detail associated with processes, such as topographic forcing, that cannot be captured by GCMs.

RegCM3 is a high resolution atmosphere model coupled to a physically based surface process model. RegCM3 is the third generation model that was originally developed in the 1980s and 1990s by the National Center for Atmospheric Research (NCAR).

RegCM3 features the following components: dynamical core, radiative transfer physics, dynamic precipitation, convective precipitation, a planetary boundary layer, a biosphere, open ocean representation, closed water bodies, and atmospheric chemistry/aerosols—all of which are coupled and interactive. RegCM3 requires time-varying vertical profiles of wind, temperature, and humidity at the model boundaries, as well as surface boundary conditions, on a 6-hour simulation interval. RegCM3 assimilates the GCM boundary conditions with exponential decay in space over 12 grid cells around the perimeter of the model domain. The biosphere-atmosphere transfer scheme simulates the surface processes related to vegetation and hydrology which vary in response to conditions in the atmosphere. The USGS has shown that RegCM3 is capable of simulating annual and seasonal climatologies that are in close agreement with historical observations.

Dynamical downscaling was carried out over six different regions (model domains). The North American domain has 50 km horizontal grid spacing with 23 vertical levels, the Eastern North America and Western North America domains have a 15 km horizontal grid spacing with 18 vertical levels. The Western North America domain was divided into four overlapping domains to achieve a balance between boundary forcing, regional dynamics, and simulation quality due to the complex regional topography. The 50-km-grid spacing for the North America domain were intended to provide for the analysis of large-scale circulation patterns and modes of variability (e.g. El Niño). The 15-km-grid spacing provides high resolution climate and surface fields that better reflect topographic forcings. Combined, the 50 km and 15 km simulations allow for the joint analysis of synoptic-scale circulation variations and the resultant surface responses.

Boundary conditions for RegCM3 were derived from historical and future climate simulations using three GCMs: GFDL CM 2.0, MPI ECHAM5, and GENMOM. Simulations from GFDL CM 2.0 and MPI ECHAM5 were obtained from the CMIP3 multi-model database (see Section 4.1.1.). GENMOM was recently developed by USGS in collaboration with Pennsylvania State University by coupling the GENESIS v3.0 atmospheric general circulation model and the MOM v2.0 ocean general circulation model. GENMOM did not contribute 20th century simulations or 21st century projections to the CMIP3 or CMIP5 multi-model datasets; however, the USGS is working with GENMOM simulations for the paleoclimate modeling inter-comparison project as part of CMIP5.

In addition to three GCMs, RegCM3 was also used to dynamically downscale historical climate conditions from the National Center for Environmental Prediction and National Center for Atmospheric Research (NCEP-NCAR) Reanalysis. The NCEP-NCAR Reanalysis was developed by using an atmospheric general circulation model to “reanalyze” historical climate conditions. In contrast to typical GCM simulations of historical climate, in which the model simulates all climate processes, the reanalysis method uses data assimilation techniques to ensure that the model is consistent with historical observations of temperature, precipitation, and other climate variables. The resulting reanalysis provides a spatially and temporally complete, internally consistent set of historical climate and land surface variables. Results from downscaling the NCEP-NCAR Reanalysis were used to evaluate RegCM3.

Usage Notes

Hostetler et al. (2011) provide a summary of the RegCM3 regional climate model, RegCM3 configuration for use in this dataset, and selection of global climate projections used in this dataset. Hostetler et al. (2011) also provide detailed instructions regarding access to this dataset of downscaled climate projections.

5. Methods for Selecting Climate Projections for Use in Detailed Analysis

Projections of future climate remain uncertain due to incomplete scientific understanding of relevant physical processes, limitations of existing modeling and downscaling methods, and uncertainties regarding future emissions pathways, among other factors. As a result, it is common practice to incorporate information from multiple climate projections to characterize subsequent uncertainties in future water supplies, demands, and relevant system performance metrics. Considering the uncertainty in future climate conditions is particularly important when evaluating planning alternatives to ensure that a selected alternative provides reliable performance in the face of an uncertain future.

As summarized above in Section 4., the scientific community has developed a number of climate projection datasets to support climate change research, risk and impact analyses, and planning and decision making. Each of these datasets provides a large number of individual climate projections from multiple GCMs and multiple emissions scenarios. In addition, some datasets include multiple projections for a single GCM and emissions scenario, each differing only in its initial state at the start of the projection. While it is important for study teams to consider uncertainty in future climate conditions, detailed analysis using all available climate projections—or even all available projections from a single dataset—in water resources, planning, and environmental analyses is generally not feasible given the practical limitations of study budget and schedule. In these cases, study teams must balance the need to consider uncertainty with practical study constraints. To do this, study teams typically choose a subset of climate projections from a selected dataset for use in detailed analysis.

The approach used to select the subset of climate projections used in a given study affects the climate projection information considered in the study and therefore the study results. Several methods have been developed to select a subset of climate projections from a given dataset for use in a detailed analysis. These methods fall into two general categories:

- **Uncertainty-based**: Selecting projections based on sampling the range of uncertainty in projected future climate (e.g., selecting projections based on the range of projected changes in annual mean precipitation and temperature; see Section 5.1.)

- **Performance-based**: Selecting projections based on GCM performance in simulating observed historical climate conditions (e.g., selecting projections based on evaluation of GCMs' ability to accurately reproduce observed 20th century precipitation and temperature characteristics over a region of interest; see Section 5.2.)

It should be noted that in addition to considering the methods summarized here, some studies make assumptions regarding future emissions trajectories and limit the projections considered for analysis based on emissions scenario. Recent studies by the scientific community have also developed methods to select or weight individual projections from a multi-model dataset based on considerations of model independence (Sanderson et al. 2015). These considerations are not discussed in detail in this document.

5.1. Methods Based on Sampling the Range of Projected Climate Change

Selecting a subset of climate projections for use in a detailed analysis by sampling the range of projected climate change is based on the premise that each of the individual projections in a given dataset is equally valid and equally likely, and that differences between projections result from uncertainties in our current understanding of the global climate system and the trajectory of future greenhouse gas and aerosol emissions.

As discussed in Section 3., the scientific community has developed a large number of global climate projections. Individual climate projections differ due to differences between the global climate models and emissions scenarios used for each projection, as well as differences between the model initial conditions at the start of a projection. Methods to select a subset of climate projections from a given dataset based on sampling the range of projected climate change assume that differences between individual climate projections stem from uncertainties that affect all climate projections, rather than from various limitations or deficiencies in the models, emissions scenarios, or initial conditions used for any given projection.

Differences between global climate models, for example, are assumed to reflect uncertainties within the climate science community regarding how best to represent the physical processes that govern the global climate system in a computer model (i.e., in a GCM). Similarly, as discussed in Section 2.2.1., differences between future emissions scenarios are assumed to reflect the vast uncertainty in future emissions. Differences between individual climate projections are therefore attributed to the numerous uncertainties inherent in projecting future climate conditions, rather than being attributed to one model or emissions scenario being more or less accurate than another. As a result, selection methods based on sampling the range of projected climate change treat each individual projection as equally valid and equally likely, and projections are selected to explicitly represent the range of uncertainty in projected future climate conditions.

Once a climate projection dataset has been selected based on the considerations discussed in Section 4., the general steps for selecting a subset of climate projections for use in a detailed analysis by sampling the range of projected climate change are discussed below.

Step 1: Define Location or Region of Interest
Study teams must define the region or location of interest for their specific study. In many cases, the region of interest is the entire river basin or sub-basin being considered. In other cases, however, a study team may choose to focus on a portion of the basin being considered. For example, in areas where spring snowmelt is the dominant source of water supply, study teams may choose to focus on the mountain headwaters as the primary source of runoff. Alternatively, in areas where water demands are concentrated in a small portion of a basin, study teams may choose to focus on the primary irrigated area(s) where the majority of water demands occur.

Step 2: Define Climate Metric(s)
Study teams must define one or more metrics that characterize climate conditions within their study area as related to their specific study objectives. In many cases, regionally-averaged or basin-averaged annual mean precipitation and temperature are sufficient to characterize climate conditions within the study area. In other cases, it may be appropriate to focus on seasonal mean precipitation and temperature for seasons of interest. For example, in areas where spring snowmelt is the dominant source of water supply, study teams may choose to focus on winter season precipitation and spring temperatures as the key climate factors that affect the amount and timing, respectively, of spring snowmelt.

Step 3: Define Historical Reference Period and Future Planning Period
Study teams must define a historical reference period and future planning period for evaluating projected changes in climate. Climate metrics calculated for the historical reference period should be representative of recent climate conditions as they relate to the specific study objectives. Projected changes in the selected climate metrics between the historical and future periods should be representative of projected climate change over the study period. Historical and future periods should be encompass a minimum of 20 years and should reflect the overall time period considered in their specific study.

Step 4: Define the Range of Uncertainty to be Considered
For each metric, study teams must define the range of uncertainty to be considered in their analysis. The range of uncertainty is typically represented as a range of percentiles that correspond to the higher end of the range of projected change, the middle or central tendency, and the lower end of the range of projected change. The central tendency is defined by the 50th percentile (median). In order to represent the range of projected climate change, the 10th and 90th percentiles, for example, encompass 80% of the values of a given metric while excluding the highest 10% and lowest 10% of values; similarly, the 20th and 80th

percentiles encompass 60% of values while excluding the highest 20% and lowest 20%. Selecting a larger range of uncertainty results in considering a broader range of future climate conditions in the study, but bears the risk of including outlier values. By contrast, selecting a smaller range of uncertainty results in considering a narrower range of future climate conditions, but reduces the risk of including outlier values. In general, selecting projections based on the 10^{th}, 50^{th}, and 90^{th} percentiles is appropriate for most studies.

Step 5: Calculate Climate Metric(s) for Historical and Future Periods
For each projection in the selected climate projection dataset, calculate the selected climate metric(s) over the selected region or location of interest for the selected historical and future periods (see Step 2 above). Metrics must be calculated consistently for each projection and time period to allow for direct comparison.

Step 6: Calculate Change in Climate Metric(s)
For each projection in the selected climate projection dataset, calculate the change in the selected climate metric(s) over the selected region or location of interest between the future and historical periods. Depending on the climate metric, the change in a metric between historical and future periods may be calculated as the absolute change (future value minus historical value), relative change (absolute change divided by historical value), or ratio (future value divided by historical value). The change in metrics based on temperature should be calculated as an absolute change, whereas the change in metrics based on precipitation should be calculated as a relative change or ratio.

Step 7: Identify Projections that Reflect the Desired Range of Uncertainty
For each variable considered, compute values of the percentiles selected in Step 4 representing the range of uncertainty to be considered. After computing percentiles for each variable, identify the projection or projections that best represent the desired range of uncertainty across all variables. Projections are commonly identified based on the Euclidian distance of each projection-specific metric from the selected percentiles across all variables considered.

If a single variable is considered, then the selected projections will simply be those that fall closest to the desired percentiles. For example, if a study team only considers the projected change in annual mean temperature and defines the range of uncertainty to be considered based on the 10^{th} and 90^{th} percentiles, then the study team will select the projections whose changes in annual mean temperature is closest to the 10^{th} and 90^{th} percentile values calculated from the overall pool of projections.

If two variables are considered, then the selected projections will be those whose changes in both variables are closest to the intersection of the selected percentiles for the two variables. For example, assume that a study team will consider changes in annual mean precipitation and temperature and a range of uncertainty in each variable based on the 10th and 90th percentiles. The study team will select projections by calculating the two-dimensional Euclidian distance of each dataset from the selected percentile values. A "hotter-wetter" projection will be selected based on having the shortest distance from both the 90th percentile change in precipitation and 90th percentile change in temperature. Similarly, a "hotter-drier" projection will be selected based on the shortest distance from the 10th percentile change in precipitation and the 90th percentile change in temperature, and so on.

5.2. Methods Based on Evaluating Model Performance in Simulating Historical Climate

Selecting a subset of climate projections for detailed analysis by evaluating model performance in simulating historical climate conditions is based on the premise that models which exhibit greater performance in simulating historical climate will provide more credible projections of future climate change.

As discussed in Section 3, the scientific community has developed a large number of global climate projections. Individual climate projections differ to due to differences between the global climate models (GCM) and emissions scenarios used for each projection, as well as differences between the model initial conditions at the start of a projection. Selection methods based on evaluation of model performance assume that some GCMs are more credible or reliable than others, and that differences between projections from different GCMs result in part from these differences in model credibility. These methods further assume that a GCM's credibility in projecting future climate conditions is directly related to its ability to simulate relevant characteristics of historical climate. These methods therefore select a subset of projections from a given multi-model projection dataset, or assign weights to individual projection in the dataset, based on evaluation of simulated climate characteristics compared to observed historical climate. In summary, selection methods based on evaluation of model performance treat some projections as more likely than others based on differences in each model's ability to reproduce observed historical climate.

Important assumptions and limitations of climate projections selection methods based on model performance are discussed in Section 3.4.

Once a climate projection dataset has been selected based on the considerations discussed in Section 4., the general steps for selecting a subset of climate projections for use in a detailed analysis by sampling the range of projected climate change are discussed below.

Step 1: Define Location or Region of Interest
Study teams must define the region or location of interest for their specific study. In many cases, the region of interest is the entire river basin or sub-basin being considered. In other cases, however, a study team may choose to focus on a portion of the basin being considered. For example, in areas where spring

snowmelt is the dominant source of water supply, study teams may choose to focus on the mountain headwaters as the primary source of runoff. Alternatively, in areas where water demands are concentrated in a small portion of a basin, study teams may choose to focus on the primary irrigated area(s) where the majority of water demands occur.

Step 2: Define Climate Metric(s) for Evaluation

Study teams must define one or more metrics for evaluation against historical observations. Climate metrics should be selected that characterize climate conditions within their study area as related to their specific study objectives. Three types of climate metrics may be considered: metrics that characterize local climate conditions or processes; metrics that characterize global climate conditions or processes; and metrics that characterize the relationship between global and local climate conditions (i.e., climate teleconnections) (Brekke et al. 2008). Metrics may represent aspects of an individual climate variable, such as annual mean precipitation or temperature over the study region; alternatively, metrics may represent the relationship between multiple variables, such as the correlation between local precipitation and a specified teleconnection index (e.g., the Niño 3.4 sea surface temperature (SST) anomaly, which is an index of the El Niño-Southern Oscillation [ENSO] teleconnection pattern).

Step 3: Define Historical Reference Period and Historical Reference Dataset(s)

Study teams must define an appropriate historical reference period over which to calculate climate metrics for evaluation, along with an appropriate historical reference dataset against which to evaluate model-simulated climate metrics. The historical reference period should typically encompass a minimum of 20 years, and the historical reference dataset(s) to provide sufficient data for a meaningful evaluation.

Step 4: Define Criteria for Selecting or Weighting GCMs Based on Evaluation

Study teams must define criteria for selecting or weighting GCMs based on evaluation results. Brekke et al. (2008) ranked models by first calculating the difference between simulations and observations for each metric and then aggregating the results into a single value for each model. Results were aggregated using a distance-based approach in which the overall "distance" between each model and the reference dataset(s) was calculated as a Euclidian distance, where each metric was treated as a dimension in the Euclidian distance formula (see Black 2006). GCMs exhibiting a shorter "distance" from observations were then selected for analysis.

Step 5: Compute Metrics and Select GCMs

Based on the criteria selected in Steps 1 through 4, compute model performance metrics for all GCMs in the selected climate projection dataset. Where a dataset includes multiple historical (20th century) simulations with the same GCM, performance metrics can be computed for each simulation and averaged over all simulations from the same model. Select a subset of GCMs to include in the analysis based on the performance criteria or rank thresholds defined in Step 4.

Step 6: Select a Subset of Climate Projections

As noted above, it may be necessary to select a subset of individual projections. Methods for selecting climate projections based on evaluation of model performance focus on selecting appropriate GCMs based on GCM performance in simulating historical climate conditions. These methods do not help study teams choose between emissions scenarios or between multiple projections from the same GCM and scenario (i.e., differing only by the model initial conditions). Additional criteria may be required to select a suitable subset of projections for analysis or to combine multiple projections from the selected GCMs.

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