Options for Improving Climate Modeling to Assist Water Utility Planning for Climate Change

WUCA
Water Utility Climate Alliance

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Prepared for:

Water Utility Climate Alliance*
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New York City Department of Environmental Protection
Portland Water Bureau
San Diego County Water Authority
San Francisco Public Utilities Commission
Seattle Public Utilities
Southern Nevada Water Authority

WUCA
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List of Acronyms and Abbreviations

AMO	Atlantic Multidecadal Oscillation
AOGCM	Atmosphere-Ocean General Circulation Model
AR4	IPCC Fourth Assessment Report
AR5	IPCC Fifth Assessment Report
BCSD	bias-correction and spatial downscaling
CCSM	Community Climate System Model
CCSP	U.S. Climate Change Science Program
C-FDDA	Climate–Four Dimensional Data Assimilation
ChiMeS	Coupled High-resolution Modeling of the Earth System
CLIVAR	climate variability and predictability
CMIP3	Coupled Model Intercomparison Project, Phase 3
CMIP5	Coupled Model Intercomparison Project, Phase 5
CO_2	carbon dioxide
COREDEX	COoperative REgional Downscaling EXperiment
CRSS	Colorado River Simulation System
CUE	Conjunctive Use Evaluation
DHSVM	Distributed Hydrology, Soil-Vegetation Model
DOE	U.S. Department of Energy
ECPC	Experimental Climate Prediction Center
EMICs	Earth Models of Intermediate Complexity
ENSO	El Niño-Southern Oscillation
ESM	Earth System Models
ESP	Extended Streamflow Prediction System
ETA	ETA Coordinate Mesoscale Model

GCM	global climate model
GFDL	Geophysical Fluid Dynamics Laboratory
GHG	greenhouse gas
GISS	Goddard Institute for Space Studies
GWLF	Generalized Watershed Loading Function model
HFAMII	Hydrocomp Forecast and Analysis Modeling System II
HH/LSM	Hetch Hetchy/Local Simulation Model
ICTS	Inter-Continental Transferability Study
IPCC	Intergovernmental Panel on Climate Change
km	kilometer
km^2	square kilometer
k/yr	thousand per year
LLNL	Lawrence Livermore National Laboratory
m	meter
mi	mile
mi^2	square mile
MM5	Mesoscale Model version 5
MPI	Max Planck Institute
M/yr	million per year
NARCCAP	North American Regional Climate Change Assessment Project
NASA	National Aeronautics and Space Administration
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Protection
NNSA	National Nuclear Security Administration
NOAA	National Oceanic and Atmospheric Administration
NRCM	Nested Regional Climate Model
NYCDEP	New York City Department of Environmental Protection
1-D	one-dimensional

PACSM	Platte and Colorado Supply Model
PCMDI	Program for Climate Model Diagnosis and Intercomparison
PDO	Pacific Decadal Oscillation
PWB	Portland Water Bureau
RAMS	Regional Atmospheric Modeling System
RCM	regional climate model
RCP	representative concentration pathway
RegCM3	Regional Climate Model version 3
RSM	Regional Spectral Model
SD	Statistical Downscaling
SEAFM	Seattle Forecast Model
SFPUC	San Francisco Public Utilities Commission
SiB	Simple Biosphere Model
SPU	Seattle Public Utilities
SRES	IPCC *Special Report on Emissions Scenarios*
STARDEX	STAtistical and Regional dynamical Downscaling of EXtremes
STM	Supply and Transmission Model
2-D	two-dimensional
UKMO	United Kingdom Meteorological Office
UW	University of Washington
VSLF	Variable Source Loading Function model
WCRP	World Climate Research Programme
WEAP	Water Evaluation and Planning model
WGCM	Working Group on Coupled Models
W/m^2	watts per square meter
WRF	Weather Research and Forecasting Model
WUCA	Water Utility Climate Alliance

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Preface

Since its creation in mid-2007, a key priority of the Water Utility Climate Alliance (WUCA) has been federally-supported climate research, both the nature and focus of the research, as well as its accessibility. This priority stems from our need to better understand the potential impacts on the water systems we manage and our commitment to develop adaptation options that address those impacts. We believe that climate research that reflects the needs of, and is accessible to, the water sector is crucial to furthering our understanding of climate change and in informing the development of appropriate adaptation options. As a result, WUCA has actively tried to advise the federal climate research program to meet these needs in as collaborative a manner as possible. We have commented on research plans of the U.S. Climate Change Science Program, we have testified on legislation regarding the creation of a National Climate Service and we have pursued other opportunities to affect federal action on climate research. Our latest effort, this white paper on climate modeling and downscaling, reflects both a continuation and an evolution of this activity.

This paper addresses a number of topics and in so doing, continues WUCA's efforts to improve our understanding of climate change. It explains how climate models work, describes how some WUCA members have used climate models and downscaling to assess impacts on their systems and develop adaptation options, and makes seven initial recommendations for how climate modeling and downscaling techniques can be improved so that these tools and techniques can be more useful for the water sector. However, a key finding of the report is that for the next few years, maybe a decade or so, significant uncertainties will remain about how climate will change at the scale utilities make decisions. In the long run, we may be able to reduce those uncertainties. In the short run, it is possible with existing technology, such as models and observations, to more completely understand the range of potential changes in climate. More importantly, the white paper represents what we hope is a catalyst for a continued dialogue between water utilities, the climate modeling and research community and federal agencies on how we can collaborate to better address the climate adaptation needs of the water sector.

WUCA and the authors of the white paper unveiled the final draft of this white paper in September 2009 at a climate modeling workshop held at the Aspen Global Change Institute in Aspen, CO. Attendees included WUCA members, global climate modelers and researchers, experts in downscaling, and federal agency staff. Over the course of the workshop WUCA members learned more about modeling efforts underway and how our recommendations are or are not being addressed through these programs, while the climate modelers learned how the water sector is using climate models to understand the implications of climate change. Members of the modeling community that reviewed this report have agreed that it is one of the best summaries of climate modeling for non-modelers. As a result of this interaction, we view this report as a starting point for generating additional discussion and feedback. We welcome your thoughts.

If you have any comments or questions about the paper, please direct them to Paul Fleming, Chair, WUCA Science and Research Committee, paul.fleming@seattle.gov, (206) 684-7626 or David Behar, WUCA Staff Chair, dbehar@sfwater.org, (415) 554-3221.

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Executive Summary

This report, which was commissioned by the Water Utility Climate Alliance (WUCA), concerns how investments in the science of climate change, and in particular climate modeling, can best be directed to help improve the quality of science so that it may be more useful to water utilities and other possible users in adapting to climate change. The main focus of this report is the identification of investments in the science of climate change that, in the opinion of the authors, can best improve the science to support adaptation.

How utilities are studying climate change and information needs

A number of WUCA members including Denver Water, the New York City Department of Environmental Protection, the Portland Water Bureau, and Seattle Public Utilities have examined climate change impacts within their water management systems. Many have used the "scenario approach," meaning they have selected at least three global climate models (GCMs), often under different greenhouse gas emissions scenarios, in conjunction with statistical and dynamic downscaling methods to capture a wide range of potential changes in climate in specific locations. Reflecting current confidence in the state of the science, most utilities did not examine probabilities of changes in climate at the watershed scale or changes in extreme events.

In general, WUCA members prefer to have climate model projections at the same space and time scales as their system models to best capture the physical processes and operations associated with their supplies. Table S.1 summarizes the scale information from the utilities. These spatial scales range from a few kilometers to thousands of kilometers. Most of the utility models for which we obtained information run on daily time steps. Even if scales aligned, many utilities would need hydrologic models to convert temperature and precipitation projections from the models to estimates of runoff and other attributes of water resources.

The science of climate modeling

GCMs model, as their title implies, global climate. They use computer codes that solve mathematical equations based on scientific understanding of the processes which govern the Earth's climate and model the atmosphere, the oceans, the land surface, and sea ice. Because of the complexity of modeling, GCMs divide the world into grid cells that are typically one hundred to a few hundred kilometers across. With such large grids, important climate processes such as thunderstorms are unresolved and modeled via simplified process models. However, such processes are incorporated into GCM downscaling tools.

Table S.1. Summary of relevant scale information from WUCA utilities

Utility	Primary utility model	Geographic scale (min)	Geographic scale (max)	Time scale (input)	Time scale (output)
Denver Water	PACSM	2.6 km^2 (470 unequally spaced model nodes)	26,000 km^2 (entire modeled region)	Daily (diversions, streamflow, demand, etc.)	Daily, monthly, and annual (streamflow)
New York City Department of Environmental Protection	GWLF, VSLF, CEQUAL-W2, UFI 1-D reservoir eutrophication, OASIS	25 km^2 (for water quality modeling)	5,100 km^2 (entire modeled region)	Daily and hourly (temperature and precipitation, solar radiation, wind speed and direction, humidity)	Daily (streamflow, nutrients and sediment loads, dissolved particulates, turbidity, phytoplankton, reservoir levels and system status)
Portland Water Bureau	DHSVM	150 m grid boxes	370 km^2 (watershed)	Daily (temperature, precipitation, and demand)	Daily (streamflow)
San Francisco Public Utilities Commission	HH/LSM	4 mi^2 (Pilarcitos reservoir watershed in Peninsula)	1,200 km^2 (Hetch Hetchy Reservoir watershed)	Monthly (runoff)	Monthly (reservoir levels, etc.)
Seattle Public Utilities	SEAFM/ HFAMII	< 1 km^2 (unequal model nodes)	203 km^2 (Masonry Dam watershed on Cedar River)	Daily minimum/ maximum for temperature and total for precipitation	Hourly/daily (streamflow, reservoir levels, etc.)
Southern Nevada Water Authority	CRSS	Unknown, but probably specific hydrographic basins	Entire Colorado River basin	Daily and monthly (temperature, precipitation, and wind speed)	Monthly and annual (streamflow and evaporative loss)

CRSS = Colorado River Simulation System; DHSVM = Distributed Hydrology, Soil-Vegetation Model; GWLF = Generalized Watershed Loading Function model; HH/LSM = Hetch Hetchy/Local Simulation Model; OASIS = a proprietary model developed by HydroLogics; PACSM = Platte and Colorado Supply Model; SEAFM/HFAMII = Seattle Forecast Model/Hydrocomp Forecast and Analysis Modeling System II; VSLF = Variable Source Loading Function.

In general, the GCMs simulate processes over large geographic areas and timescales better than processes over smaller geographic areas and timescales. Also, the models tend to simulate temperature better than precipitation, although precipitation is better modeled over large geographic areas than small areas.

Studies that look at GCM performance for many variables at once yield some useful insights:

- Climate model simulations have generally improved since the early 1990s in their ability to simulate the observed mean climate and seasonal cycle.
- Despite the increase in model performance over the last two decades, the range of climate projections across all models has not appreciably narrowed.
- The actual uncertainty of global and regional climate change (as scientists understand it) is larger than the range simulated by the current generation of models.
- The average across all models ("multi-model average") simulates observed long-term climatological averages at all scales better than any individual model due to the tendency for model errors to cancel one another. However, the multi-model average will understate potential changes in extremes.
- For many risk assessment applications, it is better to use a range of individual models, rather than a single model or the multi-model average, in order to obtain a larger range of possible outcomes.
- There is no "best" model. Individual models have different strengths and weaknesses that compensate for one another, so most models fall within a relatively narrow range of overall skill (skill is a model's ability to simulate past climate).
- The relationship between model performance in simulating current or historical climate conditions and the reliability of its projections of future changes on global and regional scales is not well understood.
- On a regional scale, culling models based on performance in simulating current climate does not necessarily yield a narrower range of projections.

Although GCMs' resolution has increased over several decades, their coarse resolution still requires the use of downscaling techniques to obtain high resolution regional and local projections. Essentially, GCM downscaling simulates the behavior of local climate processes that are absent in GCMs, such as the effects of coastlines or mountains on local and regional climate. While downscaling creates local and regional information not present in GCMs, it will not correct large-scale errors in GCMs, such as GCM simulations that contain poor depictions of the impact of El Niño on the mid-latitude storm track. Furthermore, the regional climate projections resulting from downscaling techniques may be different than those obtained had the GCM been used alone but with very high resolution. This creates some ambiguity about the consistency of the large-scale and regional-scale simulated climate processes that may be reflected in the accuracy and precision of regional climate change scenarios. As a result, methods have been developed to evaluate the veracity of regional simulations and quantify their uncertainties.

There are two main types of downscaling techniques: dynamical downscaling and statistical downscaling. Regional climate models (RCMs) are used for dynamical downscaling from GCMs and, like GCMs, are mechanistic models of the climate, but unlike GCMs they cover a portion of the world, such as the continental United States. This enables the models to be run with higher resolution and allows for better simulation of important regional processes and features, such as topography.

Statistical downscaling models develop empirical mathematical relationships between output from global climate simulations of current climate and local climate observations. For example, estimates of temperature at a particular location may be correlated with upper-level pressure patterns and wind fields. The mathematical relationships are presumed unchanged when data from GCM future climate projections are used to estimate changes in climate at a specific location. Thus, statistical downscaling methods are very effective at capturing local climate changes that are strongly tied to large-scale climate changes.

Significant improvements of GCMs to the point where their output can be input directly into water utilities planning models without bias correction and downscaling will likely take more than a decade or two. Thus, in the interim, downscaling is needed to provide climate change at the spatial and temporal scales water utilities desire. Improvements in the simulation by GCMs of large-scale climate conditions will increase the accuracy of downscaling. More extensive coordination among GCM, RCM, and statistical downscaling communities is needed to improve the usefulness of downscaled data.

Even with such improvements, it is very likely that substantial uncertainty about future climate change at these desired scales will remain. However, the community could improve how it communicates on the extent and nature of the uncertainties. Even with these remaining uncertainties, there is no doubt that climate is changing and methods exist to help utilities incorporate what is known about future climate change into planning and long-term decisions [see the WUCA paper on decision analysis (Means et al., 2009)].

What water utilities would like from climate science

In general, it is important to note that there does not appear to be a single investment – i.e., the proverbial "magic bullet" – which will substantially reduce the range of projections at the scale at which utility planning is conducted. Such projection could be used by utilities to help make decisions on expensive or long-lived investments such as infrastructure. (This is sometimes referred to as making the science "actionable" for water utilities.)

Based on our experience working with the water resources community on climate change adaptation and on our discussions with WUCA members, we identified four topics that we believe capture the improvements that are desired in the science. The four improvements follow and the prospects for improvement in the science over the next decade are discussed.

1. *Model agreement on change in key parameters*. A critical impediment to developing consistent projections of regional climate change is that GCM projections in many regions differ on how key parameters such as circulation patterns will change. A number of the options identified below concern how improvements can be made in simulating a number of these phenomena. Such improvements may take years to be realized. In the meantime, we can better understand the sources of uncertainty about regional climate change and improve techniques for analyzing and applying climate models.

2. *Narrowing of the range of model output.* The concern by utilities is that across the numerous emissions scenarios and models, a wide range of projections is given. Only modest progress is expected because two main sources of uncertainty – emissions scenarios and model climate sensitivity – have seen only slow progress in narrowing uncertainty. Enhanced use of observational data to constrain GCMs may help make progress on this matter.

3. *Climate model resolution at a spatial and temporal scale that matches water utilities' current system models.* Ideally, the resolution of GCM output would be at the same scale in utilities' systems models. The range of GCM resolution used in climate projections will likely improve over the next few years from 100–400 km to 50–200 km but for the most part this resolution will be more coarse than that currently used in utility system models. Note that increased resolution alone does not guarantee increased accuracy.

4. *Improved projections within water utility planning horizons.* While long-term projections of climate change can be useful to utilities, they are also interested in climate projections for the next few decades. However, in the first few decades of model projections, simulations of natural modes of climate variability typically have a larger effect on climate projections than GHG concentrations. Improved simulations of the drivers of climate variability, such as improved modeling of the Tropical Pacific and

decadal projections may prove helpful here. However, such improvements are likely to take years to be realized.

Options for improving modeling to create more useful and reliable projections

Two sets of options are identified: the first for GCMs and the second for downscaling. These options also fall into two other categories. One involves improving the understanding of how the climate system works, which should improve the models. We are extremely confident these improvements will happen, but improvements do not happen overnight and can take a decade or more to be realized in a manner that will be considered noticeable to water utilities and other users (i.e., make noticeable improvements in any of the four topics discussed above). The second set of options involves doing more with the climate model data that are already available. This involves improving the archiving and targeted analysis of model output (e.g., from the Coupled Model Intercomparison Project 5 just getting underway). This work can begin immediately and could produce results within a few years.

GCM options

GCM-1. Development and enhancement of global climate model ensembles. This will result in the creation of more GCM ensemble projections of at least the next 50 years, and will likely lead to increased confidence in the ranges of such projections through a better understanding of sources of uncertainty.

GCM-2. Improved use of observations to constrain climate model projections. This effort will develop and apply new methods to use observations of the past climate and the emerging climate change signal to narrow the range of climate model projections where possible. These techniques will enable better estimation of the likely range of global temperature change, and of regional patterns of climate change for temperature and precipitation.

GCM-3. Improved modeling of the Tropical Pacific. Projections for the Tropical Pacific are a primary source of uncertainty in climate projections for the Western and Central United States. This effort would combine modeling, observations, and theory with the goals of reducing climate model bias in the Tropical Pacific, and seeking convergence among model projections.

GCM-4. Improved decadal prediction. The option would develop the ability to integrate projections of climate variability, particularly decadal variability, with projections of climate change, thus addressing planning horizons from 5 to 50 years.

Downscaling options

Downscaling-1. Development of regional climate change ensembles. This effort would be an extension of option GCM-1 that would vastly improve the characterization of uncertainty and confidence in regional projections. The accessibility of these regional projections would be optimized by adopting the highly successful community archive approaches in use by climate research centers such as Lawrence Berkeley National Laboratory and the National Center for Atmospheric Research.

Downscaling-2. Development of RCM model components. This option would focus on reducing RCM disparities in representation of region-specific climate processes such as the North American Monsoon System, given accurate large-scale conditions, through development of new model components and modeling techniques.

Downscaling-3. Development of statistical downscaling techniques for probabilistic downscaling, extremes, and daily data. This effort would be best applied in tandem with option GCM-1. It would improve uncertainty estimates of local climate change for variables critical to water utilities given large-scale changes captured by using a large number of GCM projections, and it would provide a community archive as in option Downscaling-1.

Table S.2 summarizes key characteristics of each option.

In conclusion, we think that there are substantial opportunities to improve our understanding of regional climate change using information that is currently available and climate model runs that will be conducted for the Intergovernmental Panel on Climate Change Fifth Assessment Report/Coupled Model Intercomparison Project, Phase 5 exercises. We also think the climate models will improve in many ways that will lead to increased confidence in the realism of their output and be useful to water managers. However, sizable changes in addressing the four dimensions of improvement desired by water managers – model agreement, narrow projection range, spatial scale, and time horizon – will likely take a decade or more to be realized. Since uncertainty will always be present, water resource managers will need to use decision analysis – how to make the best decisions *we can* about the management of water resources given what we know and what we do not know.

Table S.2. Summary of investment options for climate models

Option	Pros	Cons	Time period	Costs
GCM investment options				
GCM-1. Develop and enhance GCM ensembles	Provide a rich set of scenarios Improve analysis of climate signal vs. model variability	More model runs require lower model resolution Storage may be limiting	2–7 years	\$3–5 M over five years for 100 km resolution \$10–30 M over five years for 50-km
GCM-2. Improve use of observations to constrain models' projections	Improve observations over time May be best hope for reducing uncertainties	May take decades Data assimilation technologically complex and computationally intensive	First results within 2 years Ocean modeling: 5–10 years Significant improvement may take longer	Research on statistical methods: \$2–5 M/yr GCM assimilation: \$2–\$10 M/yr per GCM Integration of data assimilation: \$2–10 M/yr
GCM-3. Improve tropical Pacific modeling	Might narrow precipitation projections for North America	Least chance of success Most costly option	5–15 years	Analysis: \$1–3 M/yr Modeling: \$5–10 M/yr
GCM-4. Evaluate decadal predictions	Provide more reliable projections for next few decades Enhance ability to integrate decadal variability with climate change	Predictive skill in forecasting these phenomena may be low Many methodological issues to be worked out regarding how to initialize the models	Projections could be available in 2 years	< \$1 M/yr initially; more later if science makes progress

Table S.2. Summary of investment options for climate models (cont.)

Option	Pros	Cons	Time period	Costs
Downscaling investment options				
DS-1. Develop regional and local climate change ensembles	Understand, characterize, and quantify uncertainty in regional climate projections Can enable probabilistic output Create archive of regional and local projections May trim to a less costly alternative Foster dialogue with water community	Most expensive DS option Requires high level of infrastructure, coordination, and maintenance Needs sustained investment over time	If begins within a year, results in 2–5 years	Infrastructure: \$5–10 M/yr Computing facility: \$10–15 M (one time cost) External grant program for scientific work \$10 M/yr for 5–10 years
DS-2. Develop RCM model components	Improve understanding of and reduce disparity in RCM simulations of regional processes, given accurate large-scale conditions Enable analysis of results from higher-resolution RCMs Foster dialogue with water community	Observation system may be inadequate for evaluation of high-resolution model output Output not necessarily at the scales needed by water utilities	Can begin within 1 year Many analyses done within 2–4 years	Research staff \$5 M/yr Computing facility: \$1–5 M Costs for observational system not estimated
DS-3. Develop statistical downscaling techniques	Produce a large number local climate projections of variables critical to water utilities Create archive of local projections. Can enable probabilistic output Foster dialogue with water community	Will reflect only large-scale changes; thus, probabilistic information will have incomplete representation of change	Can begin within 1 year Many analyses done within 2–4 years	Data archiving facility: less than \$1 M External grants program: \$5 M/yr for 5–10 years

k/yr = thousand per year; M/yr = million per year.

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1. Introduction

The "Uncertainty Prayer"

Grant us…
The ability to reduce the uncertainties we can;
The willingness to work with the uncertainties we cannot;
And the scientific knowledge to know the difference.

The analysis of the effects of increasing atmospheric greenhouse gas (GHG) concentrations on the world's climate has long faced a problem of dual and not necessarily consistent demands on the science of climate change. On the one hand, since Arrhenius' time (Arrhenius, 1896), scientists have tried to estimate how global climate will change as a result of increasing GHG concentrations. The most recent Intergovernmental Panel on Climate Change (IPCC) report [Solomon et al., 2007 (IPCC AR4)] presented the most definitive set of projections of change in global climate (and these projections have been revisited by the U.S. Climate Change Science Program in Karl et al., 2009). This information is very important for understanding the severity of change in climate globally. It is also useful to understand how much attempts to reduce future emissions of GHGs will limit the level of increase in global temperatures.

The second set of demands on the science concerns a desire for more precise and accurate information on change in regional climate conditions. Region is defined as ranging from multiple watersheds or counties to a multi-state area (e.g., the southwest). The desire is for better information on the consequences of climate change at a scale that is meaningful and useful to people who will (and already may) be affected by it; that is, the local and regional scale. Since the 1980s, projections of regional climate change from the leading global climate models (GCMs)[1] have been used to estimate impacts (e.g., Parry et al., 1987). Such analyses were originally undertaken to inform policymakers and the public about the potential consequences of climate change. There has also been a desire to provide information that could be of use in adapting affected systems to climate change. In recent years, the demand for information from the climate models to aid in adaptation has increased.

Over time, the resolution of climate models has improved. The IPCC (Le Treut et al., 2007) documents the increase in model resolution and other improvements. They report that model resolution has increased from about 500 kilometers (km) at the time of the First IPCC Assessment in 1990 to about 110 km in the Fourth Assessment. In addition, techniques for taking output from GCMs and estimating changes at much higher resolution have been developed and widely applied. Such "downscaling" techniques have allowed for more precision in climate

1. GCMs include general circulation models and other models.

change projections. Yet, as the models have improved, the demands for such information have also increased.

Those interested in adapting to climate change have expressed a sense of frustration that the projections on regional climate change are not precise enough to support incorporating climate change into many regional and local decision-making, particularly those involving large financial investments. The perception is that ranges of projected changes – whether in sea level rise, temperature, precipitation, or other variables – either cover too wide a range to be useful for policymaking or, as is often the case with precipitation, do not agree on whether there will be an increase or decrease. As David Behar of the San Francisco Public Utilities Commission noted at a recent workshop, the climate change projections need to become more "actionable" for water utilities to be able to act on them. He defined "actionable science" as: "Data, analysis, and forecasts that are sufficiently predictive, accepted, and understandable to support decision-making, including capital investment decision-making" (Behar, 2009).

This report, which was commissioned by the Water Utility Climate Alliance (WUCA), considers how investments in the science of climate change, and in particular climate modeling, can best be directed to help improve the quality of science so it may be more useful to water utilities and other possible users in adapting to climate change. The main focus of this report is identification of investments in the science that, in the opinion of the authors, can best improve the science to support adaptation. The report identifies specific investments and examines how they could improve the science. It also estimates the costs of the investments, how long it will take for them to yield results, and their likelihood of success.

Because it is important that a non-climate scientist understand the report's recommendations, the report describes the science of climate change modeling to help readers understand the potential investments. The report also discusses how climate information has been used by water utilities in recent assessments, and the spatial and temporal scales utilities desire to adequately model and assess their water supply systems. Finally, the report briefly addresses how climate modeling information should be used to examine water resources. This study focuses on potential improvements in GCMs and downscaling techniques, but does not address improvements in climate science regarding sea level rise, coastal ocean processes, groundwater, and glacier melt that require other types of models. Also, we do not address modeling of climate change on extreme events such as hurricanes or intense storms.

The main focus of the report is on options for improving the projections of climate change. Note however, that while improving the science can help decision-making, an important component of adaptation is making the best decisions possible in light of uncertainties. In a parallel report to WUCA, Means et al. (2009) review alternative decision-making approaches.

This report addresses questions submitted by WUCA. It first identifies key issues that the water resources community would like to have resolved to produce more actionable science. It then reviews how utilities currently use climate model output and what spatial and temporal scales water utilities desire for such output. It next turns to an overview of climate science, with an emphasis on explaining how climate models work. Finally, the report identifies options for improving the science.

1.1 What Water Utilities Want from Climate Change Models: Key Objectives

Based on our experience working with the water resources community on climate change adaptation and on our discussions with WUCA members, we have identified the following four topics that we believe capture the improvements that the water resources community desires in the science. Later in this report we provide our analysis of whether significant progress is possible in these areas.

1. *Model agreement on change in key parameters* (e.g., increase in seasonal or annual precipitation). While in some regions, such as the U.S. Southwest, most models project the same change in annual precipitation, in many U.S. regions there is too little agreement across models on whether precipitation will increase or decrease. To be sure, no model is projecting no change in precipitation patterns. All the climate models, however, project increased temperature and rise in sea levels across the United States. The issue here is how the science can be improved to create more agreement across models on projections of change in precipitation. What is desirable is not just agreement across models, but agreement with confidence (i.e., avoiding a situation where all or most of the models are "wrong").

2. *Narrowing of the range of model output.* Even for variables that all the models project increases on, such as temperature, the magnitude of projections at the regional scale varies widely. Such a wide range of projections makes it more difficult for utilities to adapt to climate change, because in many cases they cannot determine whether the consequences of changes in the variable will be significant or minor (Means et al., 2009). The matter here is how the range of projections could be narrowed.

3. *Climate model resolution at a spatial and temporal scale that matches water utilities' current system models.* One of the major concerns water utilities and others have had with climate model output is the coarse resolution from the models. GCMs typically divide the world into grid cells (sometimes called "grid boxes"; see Chapter 3) that are generally one to two hundred kilometers or more across. They simulate an average climate for each grid and cannot account for variations within each grid – and often do

not adequately account for conditions within each grid box. Regional climate models (RCMs) take "boundary conditions" from GCMs and simulate climate often to a scale of tens of miles. Even at that scale, local climate conditions are not adequately captured. Statistical downscaling can simulate climate at a particular location or over an area, but assume fixed empirical relationships between local and larger scale climate parameters. It is desirable for dynamic models (GCMs and RCMs) to produce results at a higher resolution.

4. *Improved projections within water utility planning horizons.* Climate model projections are often presented for many decades into the future (e.g., around 2100). While long-term projections can be useful to utilities, they are also interested in climate projections for the next few decades. However, in the first few decades of model projections, simulations of natural modes of climate variability typically have a larger effect on climate projections than GHG concentrations. Beyond a few decades, the signal from increased GHG concentrations becomes stronger than natural variability. The issue here is how the climate models can produce improved projections for two to three decades from the present, which would require simulation of drivers of climate variability.

It may be possible to use these four areas of model improvement as ways of gauging if improvements in the science yield changes that can be seen based on these four criteria.

2. Perspectives from Water Utilities: Current Uses of Climate Models and Desired Output Scales

2.1 What Methods Have Water Utilities Used to Analyze Climate Change Impacts on Water Resources?

Several WUCA member utilities have already engaged in studies to determine how projected changes in climate may affect their utility operations and planning needs. A brief review of these efforts is instructive, as it indicates the direction and strategy these utilities have already taken to address the potential impacts of a changing climate on their utility operations and planning.

2.1.1 Denver Water

Denver Water has engaged in several climate initiatives: a sensitivity analysis, a paleoclimate extrapolation from tree ring data, and the Joint Front Range Climate Change Vulnerability Study.

Sensitivity analysis. Denver Water conducted a simplified sensitivity analysis of how water supplies may be affected by climate change using a hydrology model and Denver Water's Platte and Colorado Supply Model (PACSM) water allocation model. Denver Water worked with the Colorado River Basin Forecast Center using the Sacramento Soil Moisture model coupled with the Anderson Snow-17 model to calibrate Blue River basin streamflows using historical temperature and precipitation to mimic historic streamflows. They then ran a sensitivity analysis by altering temperature to determine percentage changes in Blue River streamflow, and applying those same delta streamflows to the South Platte, Fraser, and Williams Fork basins. These altered streamflows were then fed into PACSM to determine the effect on Denver's water supply. The sensitivity analysis included runs for (1) a 5°F (3°C) temperature increase, and (2) a 2°F (1.1°C) temperature increase, with no precipitation change. This analysis found that a 2–5°F (1.1–3°C) increase in temperature could cause a 7–14% decline in water supply yield. The hydrology models adjusted historical streamflows using forecasted temperature changes. Ultimately, Denver Water determined that using the delta streamflows for the Blue River basin as a proxy for Denver Water's other basins was insufficient, which led to the Front Range study described below (Robert Steger, Manager of Raw Water Supply, Denver Water, personal communication, June 3, 2009).

Paleoclimate reconstruction. Model reconstructions of 400 years of streamflows using tree ring data (Woodhouse and Lukas, 2006) were completed within Denver Water's collection system. This provided Denver Water with a broader perspective on vulnerability due to natural variability within the climatological record. The adjusted streamflows were analyzed in PACSM to quantify potential impacts to Denver's water supply should severe prehistoric droughts be repeated. This gave Denver Water a broader perspective of climate vulnerability based on historical drought conditions that exceed anything in the instrumental record.

Joint Front Range Climate Change Vulnerability Study. Denver Water leads the Joint Front Range Climate Change Vulnerability Study in cooperation with the City of Aurora, the City of Boulder, Colorado Springs Utilities, the City of Ft. Collins, and the Northern Colorado Water Conservancy District. Other water agencies, including the Colorado Water Conservation Board, the Water Research Foundation, and the Western Water Assessment – a joint effort between the University of Colorado's Cooperative Institute for Research in Environmental Sciences and the National Oceanic and Atmospheric Administration's (NOAA's) Earth System Research Laboratory also participate in this effort (Laurna Kaatz, Climate Scientist, Denver Water, personal communication, April 1, 2009). This project focuses on assessing potential changes in the timing and volume of runoff from selected climate change scenarios centered about the years 2040 and 2070, using 1950–1999 natural streamflow as a baseline. The project partners are calibrating two hydrologic models – the Water Evaluation and Planning model (WEAP) with the National Center for Atmospheric Research (NCAR) and the Anderson Snow Model and Sacramento Soil Moisture Model with Riverside – as the primary tools to convert statistically downscaled temperature and precipitation data from GCMs into streamflow, which can then be used by the individual water utilities in their own operational system models.

This project focuses on assessing potential changes in the timing and volume of runoff by selecting five model runs from the total of 112 statistically downscaled GCM runs available for the region (Maurer et al., 2007). The runs selected were based on idealized hot and dry (90th percentile temperature, 10th percentile precipitation – all percentiles refer to the distribution of the 112 scenarios), hot and wet (70th percentile temperature, 70th percentile precipitation), warm and dry (30th percentile temperature, 30th percentile precipitation), warm and wet (10th percentile temperature, 90th percentile precipitation), and median (50th percentile temperature, 50th percentile precipitation) scenarios. These scenarios were chosen to incorporate a wide array of model run results without being extreme, and to make sure the model run selection process was straightforward and easily repeatable. The project compares baseline data from 1950 to 1999 with two projections averaged over 30 years centered around 2040 and 2070. Average monthly temperature and precipitation projections will be used to calculate changes in hydrology for the complete grid of the study area (Laurna Kaatz, Climate Scientist, Denver Water, personal communication, August 14, 2009). The project partners are calibrating two hydrologic models – the Water Evaluation and Planning model and the Sacramento Soil Moisture model coupled with the Snow-17 model – as the primary tools to convert statistically downscaled temperature and precipitation data from GCMs into streamflow, which can then be used by the individual water utilities in their own operational system models.

2.1.2 The New York City Department of Environmental Protection

The New York City Department of Environmental Protection (NYCDEP) worked with researchers from Columbia University's Center for Climate Systems Research to design its Climate Impact Assessment project (Major et al., 2007). The goal of this integrated modeling project is to estimate the effect of future climate change on the quantity and quality of New York City's water supply. The project is based on three core questions of interest to NYCDEP, including the potential effects of climate change on (1) total water supply, (2) turbidity, and (3) eutrophication. The project will combine the use of climate change predictions, NYCDEP water quality and water supply models, and analytical measures of system performance to advance NYCDEP's understanding of the potential impacts of climate change on the water supply system.

The project is planned in two phases. Phase I, currently underway, is aimed at providing a first-cut evaluation of the effects of climate change on water quantity and quality in selected portions of the water system, using the existing modeling system and data available from three GCMs. Phase II will have similar goals as Phase I, but with upgrades to both models and datasets applied to the entire water supply system.

A climate change scenario framework was developed for the New York City water supply system using high-temporal-resolution data from the Program for Climate Model Diagnosis and Intercomparison (PCMDI) web site maintained by the Lawrence Livermore National Laboratory (LLNL) in Berkeley, California (Maurer et al., 2007). Data for Phase I were extracted from the single grid box at the center of the watershed region. Baseline data for 1981–2000 came from "hindcast" model runs, while data for 2046–2065 and 2081–2100 came from three GCM models [the Goddard Institute for Space Studies (GISS) ModelE, the Max Planck Institute (MPI) ECHAM5, and the NCAR CCSM3] coupled with three *Special Report on Emissions Scenarios* (SRES)[1] scenarios A1B, A2, and B1. The data included mean temperature, maximum temperature, minimum temperature, precipitation, sea level pressure, zonal wind, meridianal wind, solar radiation, longwave radiation, and dewpoint temperature.

For Phase I, each scenario was used to calculate delta change coefficients representing mean monthly change in air temperature and precipitation between control and future prediction periods. Delta changes factors were applied additively for air temperature and as a ratio for precipitation to the historical control period data, generating a future prediction time series. The possibility of applying the delta change method to the wind and solar radiation data needed for the reservoir models is being investigated. It is anticipated that for Phase II, climate inputs will be refined using advanced delta change, statistical, and/or RCM downscaling techniques.

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1. The IPCC SRES outlines multiple equally possible socioeconomic futures that account for future trends in greenhouse gas pollution, land use, technological development, and economic development.

Models currently employed that will be used for the integrated modeling project include: the Variable Source Loading Function model (VSLF); a 1-dimensional reservoir eutrophication model; a 2-dimensional reservoir turbidity transport model (CEQUAL-W2); and the OASIS system operations model for the entire water supply. These four models taken together with the existing and in-progress climate scenarios make the proposed integrated assessment possible. (See Appendix A for further explanation of these models.)

As the project progresses, further model enhancements and integration will be implemented. For the watershed model this includes improvements to the following model elements: hydrologic balance, sediment and nutrient generation and transport, ecosystem effects, and land use. For the reservoir models this includes additional upgrades and calibration and development of response function models keyed on system performance measures. For the integrated system this includes enhanced coupling of the watershed and reservoir models to OASIS. And for model inputs this includes advanced delta change with historical data morphing, statistical downscaling, and RCM simulations.

The project will yield a better understanding of system dynamics under an altered climate. A number of performance measures related to water system quantity and quality will be developed and used to estimate climate change effects, including total water quantity, probabilities of refill, probabilities of drawdown, key point turbidity levels, frequency of alum use, reservoir phosphorus and chlorophyll concentrations, and restrictions in water use due to eutrophication. The results of this project will provide the basis for recommendations about system operation now and in the future, and, in later phases, recommendations about required infrastructure changes and improvements.

2.1.3 Portland Water Bureau

The Portland Water Bureau (PWB) worked with the University of Washington (UW) to develop a climate change study for the Bull Run watershed in the transient snow zone west of Mt. Hood (Palmer and Hahn, 2002). This study was conducted in 2001 and completed in 2002. For this study, PWB evaluated four GCMs selected to represent a range of temperatures and precipitation patterns for the Pacific Northwest: the NCAR's Parallel Climate Model, MPI's ECHAM4 model, and the United Kingdom Meteorological Office's (UKMO's) HadCM2 and HadCM3 models. Model projections of average monthly temperature and precipitation values for the 2020 and 2040 decades were used in the analysis. The four GCMs were downscaled from a multi-degree to a one-degree scale using the Symap algorithm, an interpolation technique. The results of these climate model runs were discussed individually, and were not aggregated into any kind of distribution function. Consequently, the study is a classic scenario analysis and is presented as such.

This study explores the impact that climate change will have on the Bull Run watershed and PWB's ability to provide reliable water to its customers. It uses a series of linked models to address the potential impacts of climate change on hydrologic processes and management of the water supply system. The results of this study also included an evaluation of the impacts of changes in temperature on water demand. The PWB has used this study as a first look at how climate change might impact both water supplies and demands. This study has been cited as part of water rights extensions for the PWB's secondary groundwater supply as well as development of a Habitat Conservation Plan for Endangered Species Act listed fish in the Bull Run watershed.

Changes in temperature and precipitation were used as inputs into a Distributed Hydrology, Soil-Vegetation Model (DHSVM) developed for PWB to simulate hydrologic processes in 150-meter grid boxes with physical data layers that are unique to the watershed. The output of DHSVM is streamflow data. These data, in turn, are fed into PWB's Supply and Transmission Model, a system operation model used in this study to examine the impacts of climate change on the water supply performance of the existing system, as well as two planning scenarios from the Infrastructure Master Plan.

This study concluded "that climate change will have a significant impact on the hydrology of the Bull Run watershed and will impact the safe yield of the Portland water system." Finally, PWB indicated an interest in repeating its climate change study using the DHSVM again, but with either using the UW Climate Impacts Group RCM outputs as parameters for input to the DHSVM (because the RCM attempts to do a better job of the storm track/topography factors for watersheds where the ocean conditions are very important), or using more GCMs than the four used in the Bull Run watershed study (Lorna Stickel, Water Resources Planning Manager, Portland Water Bureau, personal communication, April 24, 2009).

2.1.4 Seattle Public Utilities

Seattle Public Utilities (SPU) partnered with King County, Washington; the UW Department of Ecology; and Cascade Water Alliance to fund the UW Climate Impacts Group to conduct a downscaling study of three potential future climate scenarios in November 2007 (Polebitski et al., 2007). Three scenarios were used: a warm scenario – GISS ER, with SRES emission scenario B1; a warmer scenario – ECHAM5, with SRES scenario A2; and a warmest scenario – IPSL_CM4, with SRES scenario A2. These three scenarios produced future, climate-altered, meteorological datasets for the Puget Sound region at four different time periods: 2000, 2025, 2050, and 2075. These meteorological datasets were run through the DHSVM hydrology model to produce hydrologic datasets for the four time periods. This project utilized a statistical downscaling approach that produces long records – 77 years – of hydrologic and meteorological data for each climate scenario. SPU subsequently fed the hydrologic data directly into its Conjunctive Use Evaluation systems model, rather than running the raw climate model output through SPU's hydrology model – the Seattle Forecast Model (SEAFM). This allowed SPU to use a scenario approach to determine the effects of different potential climate futures on the operation of the SPU water system (Seattle Public Utilities, 2009).

SPU then explored adaptation scenarios by investigating intra-system modifications, mostly the elimination of conservative assumptions from their system supply calculations that effectively increased the usable storage capacity for water with no new supply infrastructure. While the climate scenarios reduced supply to between 79% and 94% of historic levels by 2050, these adaptations would restore between 9% and 16% of supply. Consequently, these adaptive actions would mitigate for the loss of supply in two of the three climate scenarios by 2050, but additional adaptive measures would be needed for the third climate scenario in 2050 and all three climate scenarios by 2075 to restore supply to historic levels. SPU identified potential options for these additional adaptive measures.

SPU also examined the impacts of the three climate scenarios on water demand by using a historical regression analysis of monthly data for consumption, maximum temperature, and rainfall at SeaTac Airport. Assuming that this relationship would hold into the future, SPU projected that peak season consumption could increase 4% to 13% between 2000 and 2075 under the three climate change scenarios assuming no additional demand management or conservation programs.

In a separate study, SPU engaged Northwest Hydraulic Consultants in a dynamic downscaling study (Northwest Hydraulic Consultants, 2009) that took outputs generated by two GCMs/scenario combinations – CCSM3 under an A2 scenario and ECHAM5 under an A1B scenario – and used them as inputs in the UW's Weather Research and Forecasting RCM (WRF). The GCM output consisted of meteorological data developed for two 31-year periods: one for 1970–2000 and one for 2020–2050. The WRF output was produced in two grid sizes: 20 km^2 and 36 km^2. The output of these models was fed into the Hydrologic Simulation Program-Fortran hydrologic model for the entire Thornton Creek basin to determine changes in a number of creek flow parameters. This study concluded:

> While this pilot study demonstrates the feasibility of applying such temporally and spatially detailed data to assess climate change effects on urban streams and drainage infrastructure, future projections of both precipitation and stream flow from different GCM-RCM combinations are widely divergent and there appears as yet to be insufficient information or knowledge to demonstrate that one model combination is more or less accurate than another. Additional work is needed to improve confidence in future projections and before applying dynamically downscaled data to stormwater planning, policy, or design standards (Northwest Hydraulic Consultants, 2009, p. 22).

2.1.5 Summary of analysis by utilities

The four utilities that provided information used what can be called a "scenario" approach (Means et al., 2009), which applies several climate change scenarios to capture a relatively broad range of potential climate changes. The utilities attempt to capture a range of outcomes across GCMs, but typically do not include the most extreme model results. They have tried to avoid selecting GCMs with similar regional projections. Probabilistic-based scenarios (meaning scenarios that incorporate the output of many different climate models and/or varying estimates of temperature sensitivity to GHG concentrations) do not appear to have been applied by any of the water utilities.

2.2 Analysis of Desired Spatial and Temporal Resolution Based on Utility Planning Models

The following insights on the desired scale of climate model output have been gleaned from personal communications with representatives from Denver Water, the NYCDEP, the PWB, the San Francisco Public Utilities Commission (SFPUC), and SPU. The key question of interest is how the outputs of climate models could provide useful inputs for water utility planning purposes. Specifically, this section discusses the scale at which utility models operate. It also addresses how utilities use information about climate change from climate models.

- Generally, all water utilities have multiple models that perform different functions. Each model requires different inputs at different scales, and may or may not be capable of using temperature and precipitation outputs from climate models.

- Models of water utility systems typically use streamflow as the primary input, whereas hydrologic models use meteorological variables, such as temperature and precipitation, as the primary inputs. This distinction is important because outputs from climate models (e.g., temperature and precipitation) cannot be directly used in most water utility models. Linking climate models to water utility models is technically possible if the utility model is integrated with a hydrology model that uses temperature and precipitation or other climate model outputs as input variables. Generalizing this linkage across utilities, however, poses many challenges, mostly because of the multiple types of models utilities use (e.g., operational, system, hydrological, water quality) and because the input variables for these models often varies dramatically (e.g., along spatial or temporal scales).

- The geographic scale of watersheds modeled by WUCA member utilities is generally on the order of hundreds of square kilometers. In some cases, a single point observation for temperature and precipitation will be extrapolated to the entire basin. In other cases, the basin is subdivided into much smaller components (e.g., a fraction of a square kilometer) that may incorporate single or multiple observations. Consequently, the desired resolution of climate model output may differ substantially across utilities.

- Water supply mass balancing models that integrate hydrologic models, such as Seattle's SEAFM or NYCDEP's integrated modeling project currently under development, seem to be most capable of incorporating climate model projections. The necessary inputs for this subset of utility models (i.e., meteorological variables such as temperature and precipitation) are climate model outputs, and downscaling methodologies can provide data at the scale of these operating models. However, it should be noted that for some regions, particular processes, such as coastal storms, are very important for the mass balance model, but may not be captured by climate models.

- Many utility modeling efforts appear to correlate observed variables, such as temperature and precipitation, with observations or modeled values for the output variable of interest – usually streamflow. This is typically done in spreadsheets, standalone mass balancing models, or hydrology models. Because many of these models are based on correlations with observed data, the modeled relationship, though historically true, may not be true in the future due to potential nonlinear changes in the relationship between the variables of interest as climate changes. Nevertheless, because in many cases these models are updated with new data every year, it may be possible for utility models to adjust over time to changing climate conditions.

- Water quality models may require advances in climate models to be of practical use because they operate on a finer scale than climate models and they sometimes incorporate variables not well replicated by current climate models (e.g., cloud cover, intense precipitation events) to approximate total dissolved solids, turbidity, etc. Higher-resolution or more physically accurate modeling may be necessary to capture the climatological/weather events of interest for modeling water quality. Furthermore, there may not be sufficient water quality data (e.g., particle counts, total dissolved solids) with which to calibrate climate model outputs.

- Sometimes hydrologic models and operational (mass balance) models are integrated, and sometimes they are not. When they are integrated, basic meteorological variables are used as inputs into the hydrologic models, which then produce streamflow or similar data for use in the operational models. If the operational models (requiring streamflow data) are not integrated or not available at all, substantial challenges exist in translating basic meteorological variables into streamflow or similar data. Other important variables that may need to be derived from or in addition to climate models to support utility modeling under changing climate conditions include snowpack, groundwater levels, and water demand.

Table 2.1 summarizes the scale information from the WUCA utilities. More detailed information about each utility is presented in Appendix A.

Table 2.1. Summary of relevant scale information from WUCA utilities

Utility	Primary utility model	Geographic scale (min)	Geographic scale (max)	Time scale (input)	Time scale (output)
Denver Water	PACSM	2.6 km^2 (470 unequally spaced model nodes)	26,000 km^2 (entire modeled region)	Daily (diversions, streamflow, demand, etc.)	Daily, monthly, and annual (streamflow)
New York City Department of Environmental Protection	GWLF, VSLF, CEQUAL-W2, UFI 1-D reservoir eutrophication, OASIS	25 km^2 (for water quality modeling)	5,100 km^2 (entire modeled region)	Daily and hourly (temperature and precipitation, solar radiation, wind speed, and direction, humidity)	Daily (streamflow, nutrients and sediment loads, dissolved particulates, turbidity, phytoplankton, reservoir levels, and system status)
Portland Water Bureau	DHSVM	150-m grid boxes	370 km^2 (watershed)	Daily (temperature, precipitation, and demand)	Daily (streamflow)
San Francisco Public Utilities Commission	HH/LSM	4 mi^2 (Pilarcitos reservoir watershed in Peninsula)	1,200 km^2 (Hetch Hetchy Reservoir watershed)	Monthly (runoff)	Monthly (reservoir levels, etc.)
Seattle Public Utilities	SEAFM/ HFAMII	< 1 km^2 (unequal model nodes)	203 km^2 (Masonry Dam watershed on Cedar River)	Daily minimum/ maximum for temperature and total for precipitation	Hourly/daily (streamflow, reservoir levels, etc.)
Southern Nevada Water Authority	CRSS	Unknown, but probably specific hydrographic basins	Entire Colorado River basin	Daily and monthly (temperature, precipitation, and wind speed)	Monthly and annual (streamflow and evaporative loss)

CRSS = Colorado River Simulation System; DHSVM = Distributed Hydrology, Soil-Vegetation Model; GWLF = Generalized Watershed Loading Function model; HH/LSM = Hetch Hetchy/Local Simulation Model; OASIS = a proprietary model developed by HydroLogics; PACSM = Platte and Colorado Supply Model; SEAFM/HFAMII = Seattle Forecast Model/Hydrocomp Forecast and Analysis Modeling System II; VSLF = Variable Source Loading Function.

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3. The Science of Climate Modeling

This chapter discusses the science of climate modeling with a focus on creating a sufficient understanding of the state of modeling to enable readers to understand the options for improving climate modeling. The first subsection concerns GCMs, and the second addresses downscaling. This section is not intended to serve as a comprehensive primer on the science of climate change, or climate modeling, but as a selective primer of use to water utility managers, planners, engineers, and scientists.

3.1 Global Climate Models

3.1.1 What is a GCM?

A GCM is a set of computer codes that solve mathematical equations based on scientific understanding of the processes that govern the Earth's climate. GCMs are used to simulate the climate of the past, to project future climate change, and to provide input to downscaling techniques. This section briefly explains how a GCM is constructed, and introduces some terminology and concepts on which this report's recommendations are based.

A climate model must be of global scope in order to simulate the Earth's climate – particularly how all its interlocking pieces will change over time and react to the changes humans are causing. A climate model must also be comprehensive enough to cover all the processes that are important on the time scales of the simulations. The current Atmosphere-Ocean General Circulation Models (AOGCMs) are made up of component models of the atmosphere, the oceans, the land surface, and sea ice. These component models are coupled together, enabling processes in one model to interact with other models (Figure 3.1). Versions of these component models have been developed and are continually refined at more than a dozen scientific research centers worldwide. For the most part, the recommendations in this report will refer to the atmosphere and land surface components of the GCMs, because improvements in these areas were judged to have a more direct impact on the usability for water resources. Nonetheless, all components are integral to creating a good simulation of the Earth's climate over the next century.

Climate models that also include a coupled model of the carbon cycle (and other chemical cycles important to climate) are often referred to as Earth System Models (ESMs). ESMs explicitly model the uptake and release of carbon dioxide (CO_2) and other GHGs by vegetation and by biological and chemical processes near the surface of the ocean (Figure 3.1). ESMs are necessary for emissions-driven climate projections where the resulting concentrations of GHGs are

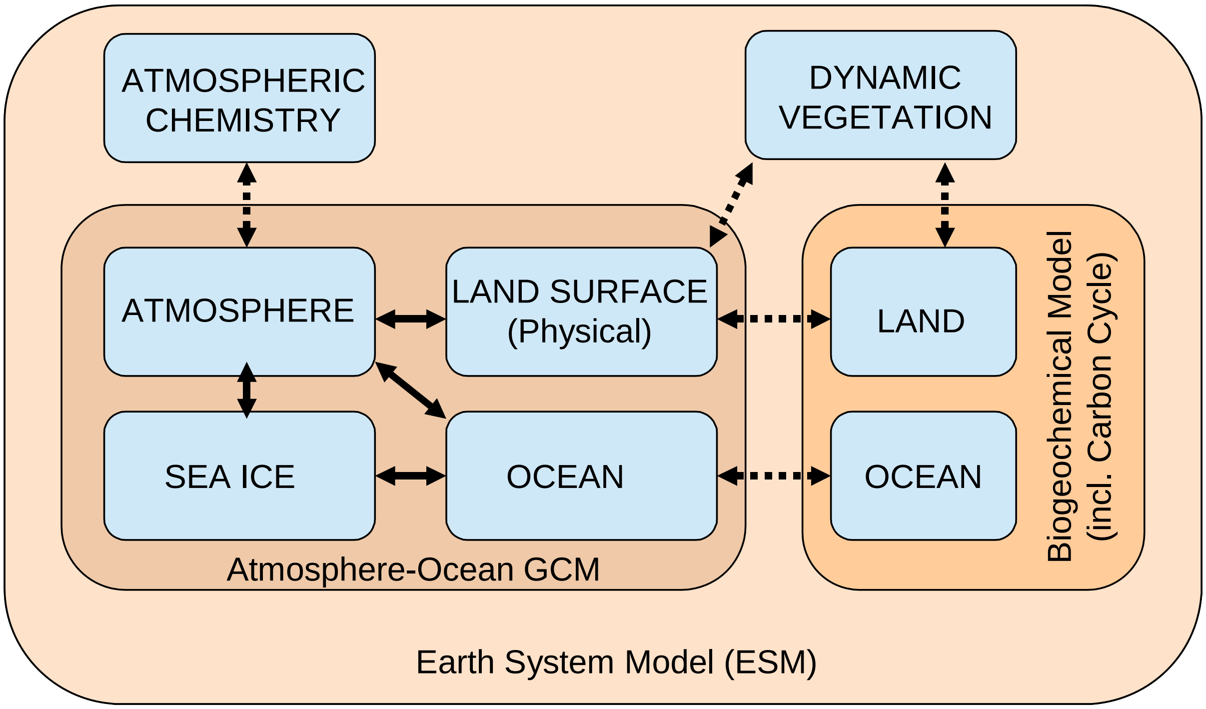

Figure 3.1. The component models that make up an AOGCM and a typical ESM used for climate simulations. Solid arrows represent flow of energy, water, and (in the case of an ESM) GHGs and other atmospheric constituents between component models. Dashed arrows represent the exchange of information within the extended Land, Ocean, and Atmosphere models that make up the ESM. Biogeochemical cycle models include the Carbon Cycle, Nitrogen Cycle, and processes in vegetation, soils, and the upper ocean that model the sources, sinks, and exchange of carbon dioxide, methane, nitrous oxide, and other important GHGs.

calculated in the model, rather than being specified as part of an input scenario to an AOGCM. The first AOGCMs were developed in the 1970s, and subsequent generations have been used to inform all four IPCC Assessments. Comprehensive ESMs are much newer, having been developed mainly during the past decade. Both AOGCMs and ESMs will be evaluated in the upcoming IPCC Fifth Assessment Report (AR5).[1]

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1. Another class of models, Earth Models of Intermediate Complexity (EMICs), can be thought of as simplified, lower resolution AOGCMS and ESMs that are used for projections longer than a century. They are of limited use for guiding climate change adaptation and are not discussed in this report.

Precipitation, wind, cloudiness, ocean currents, air, and water temperatures – these and other climate variables evolve in time and space governed by physical, chemical, and biological processes. We refer to these as mechanistic processes to distinguish them from purely empirical relationships that may be found in data without reference to an underlying mechanism. The mechanistic processes included in the climate models are quite varied – from evapotranspiration to cloud formation, the transport of heat and water vapor by the wind, infiltration of surface water into the soil, turbulent mixing of air and of the ocean waters, and so on. To the climate modeler, these processes all have one thing in common: they can be expressed in terms of mathematical equations derived from a combination of scientific laws, empirical data, and observations. These equations are then converted into computer code, along with information about the Earth's geography – such as the distribution of vegetation and soil types and a digital elevation model of topography – to form the basis for a climate model. AOGCMs are driven by the observed time history and future projected changes in incoming solar radiation, GHG concentrations, and aerosols given off by volcanic eruptions and human activities.

The variables of a climate model are marched forward at discrete time intervals, or "timesteps." Timesteps can range from a few minutes to an hour, depending on the spatial resolution of the model. As a result, GCMs simulate hourly and daily weather, and climate statistics are computed from climate models just as they are from observations.

Because of the complexity of the mathematical equations in climate models, these equations can only be solved approximately, even on the most powerful supercomputers. To determine the most precise results within this limitation, GCMs typically divide the globe – the atmosphere and the oceans – into a horizontal and vertical grid, creating so-called "grid boxes" or "grid cells" (Figure 3.2). The finer the grid, the higher the *spatial resolution*, and the more computer power required to run the simulations. The *horizontal resolution* is typically cited as representative of a component model's overall spatial and temporal resolution. The individual component models do not typically have the same spatial resolution or timestep, and may in fact have very different grid representations to better accommodate their unique physical processes. These differences are taken into account when the components are coupled.

Many climate phenomena, such as thunderstorms, take place at spatial scales smaller than a model grid cell – be it in a GCM or even a RCM. The idea of *parameterization* is to account for the effect that small-scale processes have within the grid cell through a representation of the phenomena. One way to accomplish this is through a simplified mechanistic model, or conceptual model. For example, given the grid-scale temperature lapse rate and moisture convergence in the atmosphere, a conceptual model of atmospheric convection can compute the expected total amount of convective rainfall within the grid cell, which then affects the moisture and heat fluxes at the grid scale.

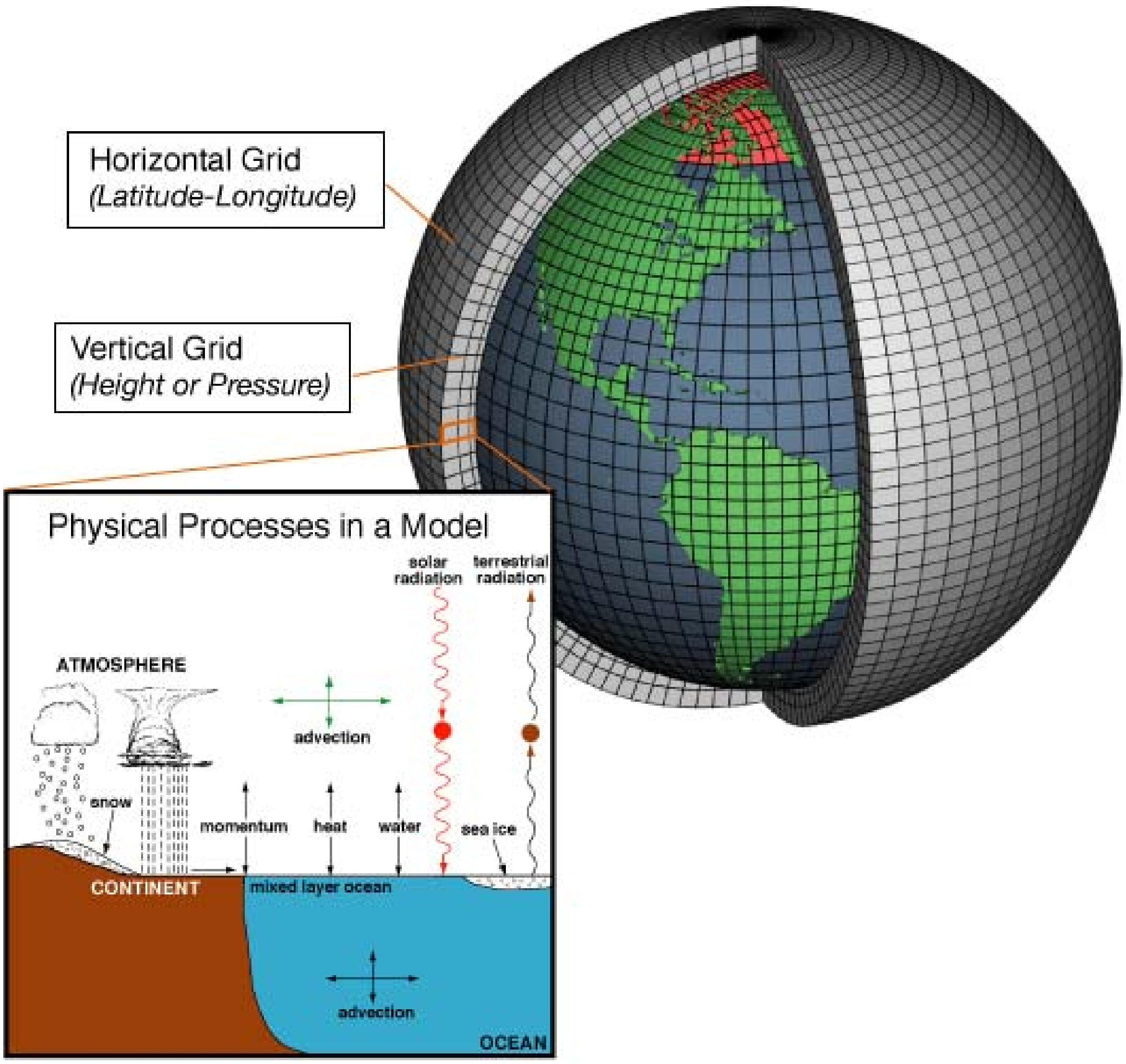

Figure 3.2. The atmosphere, ocean, land, and sea ice component models of an AOGCM are divided up into grid cells in the horizontal and vertical. The processes that are modeled within a column of grid cells is shown in the inset. Some of these processes, such as advection (transport of heat and momentum by the winds and currents) take place at the grid scale, while others such as thunderstorms are parameterized.

Source: NOAA, 2008.

In practice, parameterizations are developed from conceptual models, from empirical relationships based on observations from historical datasets, field experiments, and satellites, and from simulations with specialized higher-resolution models. Parameterizations are "universal" in that they are applied the same way in all grid cells within a model. There is not, for example, a separate parameterization of convective rainfall for Iowa and for the Amazon Basin. In the end, however, most parameterizations are highly empirical (CCSP SAP 3.1, 2008).

Many of the output variables of interest to water managers (see Table 5.1) are calculated in one or more of the model parameterizations. The strengths and weaknesses of these parameterizations are summarized in Table 3.2. The choice at a particular modeling center of the conceptual model and the way it is empirically adjusted in developing a parameterization scheme can have a sizable impact on a model's climate simulations.[2]

The need for parameterization is closely related to the spatial resolution of the GCM. A change in model resolution may require adjusting, or even completely replacing, a parameterization scheme. As model resolution improves, it may become possible to explicitly model the small-scale processes, eliminating the need for a particular parameterization. See Section 3.1.11 and Table 3.3 for more information on spatial scale, climate phenomena, and parameterizations.

The models generate enormous amounts of data output that could easily amount to hundreds of terabytes for a single run. Only a subset of the output, such as the daily or monthly average values, is saved (archived). Navigating these archives can be daunting to the non-specialist. Fortunately, only a relatively small number of a climate model's variables are directly related to water resource applications, and this report recommends data archiving enhancements that would better serve water utilities' needs.

3.1.2 How are climate projections generated, and how do they differ from predictions?

Common methodologies have been developed for making climate projections as part of a series of intercomparison projects. CMIP3 (Coupled Model Intercomparison Project, Phase 3; Meehl et al., 2007b; Lawrence Livermore Laboratory, 2009) provided the comprehensive archive of model simulations analyzed in support of the IPCC Fourth Assessment Report (Solomon et al., 2007). The climate projections in CMIP3 were generated in the following steps:

2. One caveat, besides the immediate concern about how well GCMs replicate the real world, is that climate system uncertainty is generally larger as the spatial scale of interest is reduced. The climate dynamics impacting a station observation generally have greater variability than climate dynamics impacting a large region, like the Pacific Northwest, which in turn have greater variability than climate dynamics impacting the entire Northern Hemisphere, and so on. Thus, a direct comparison of GCM output to station observations without the appropriate statistical processing is an apples-to-oranges comparison of climate system uncertainty.

1. The model is first run with constant pre-industrial values of forcing parameters (e.g., GHG concentrations) for many hundreds of simulated years, until the model's climate has reached equilibrium during the so-called "spin-up" period. The long time scale is mainly due to slow ocean processes.

2. Once the model is spun up, this run is continued, typically for several hundred simulation years without reference to actual calendar dates, and is referred to as the *pre-industrial control run*.

3. The actual time histories of all known forcing parameters are then specified, starting in the late 1800s up to the present to create *historic climate simulations* that are used for model validation.

4. The runs are continued into the future, using scenarios of future GHG concentrations and other projected forcings, to create *climate projections*.[3]

This well-established methodology has been repeatedly tested over the last three IPCC assessment cycles. An important advantage is that the control run is in equilibrium, so that the sensitivity of the model to climate forcing can be precisely estimated. However, these "free-running" climate simulations and projections are not periodically reset to observed values the way that weather prediction models are. One consequence is that the modes of variability – including model-simulated El Niño-Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), and Atlantic Multidecadal Oscillation (AMO) – are not in the same phase as observed. For example, the phases of ENSO and PDO in the historic climate simulations do not happen in the same calendar years as in observations. Climate projections are therefore more suited to looking at averages (or other statistics) computed over long time periods, or over ensembles of many model runs. Therefore, the climate projection methodology is useful for modeling how climate statistics change under the influence of different climate forcings over many decades, but are not as useful for predicting the precise evolution of the climate over the next decade or two. The "free running" nature of these projections has an important implication even for longer-term changes: one can over- or under-estimate the rate of climate change by looking at the changes in a single model run, because that particular run may have started from a different phase of variability than seen in observations.

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3. Solomon et al. (2007) notes "The inclusion, magnitude and temporal evolution of the remaining forcing agents [other than the major GHGs and sulphate aerosols] listed in Table 10.1 were left to the discretion of the individual modelling groups. These agents include tropospheric and stratospheric ozone, all of the non-sulphate aerosols, the indirect effects of aerosols on cloud albedo and lifetime, the effects of land use and solar variability" (Meehl et al., 2007a, p. 755).

Methodologies for decadal climate *prediction* (as opposed to climate *projection*) are being developed where the model variables are started from observed values (e.g., Smith et al., 2007). It is particularly important that the ocean variables be initialized correctly. These methods will produce forecasts that, in theory, include the correct phase of decadal modes. In addition, a set of "hindcasts" (forecasts begun at past dates) will be produced to evaluate the potential skill of the method. This endeavor is still young, and many basic methodological issues are still being worked out. In addition, shifts in decadal modes such as the AMO and PDO are actually quite irregular, and tend to be poorly understood and modeled, so they are difficult to predict. This is a promising area, but with many unknowns. It will be a major focus of the Coupled Model Intercomparison Project, Phase 5 (CMIP5) coordinated climate change experiments described below. The demonstrated skill may turn out to be small, but if this prediction effort proves successful, the benefit to water utilities' planning efforts could be very large.

As climate modeling develops, the goal is to use scenarios of future GHG emissions directly to force the climate models, requiring the carbon cycle and other chemical cycles to be modeled explicitly in addition to all the processes included in an AOGCM. These ESMs will be critical in furthering scientific understanding of uncertainties due to carbon-cycle feedback. However, carbon-cycle modeling is a relatively young field, and the processes involved are not as well understood as those in the atmospheric and ocean models. History has shown that as new component models are added, the simulation accuracy can decrease at first, as quantities that were fixed in the old model are allowed to vary in the new one.

For the purposes of guiding adaptation planning on the time horizons of most water utility planning, AOGCMs are sufficient, though output from both types of models can be used. This was not an issue for the CMIP3 archive of AOGCM projections forced by GHG concentrations (that were derived from SRES emissions scenarios such as B1, A1B, and A2). How to interpret a mix of projections from AOGCMs and ESMs will be an issue in the upcoming CMIP5 model projections, as noted in the next section.

3.1.3 What are the plans for CMIP5?

A major advance in climate modeling happened in the mid-1990s with the development of model intercomparison projects. These projects establish common methodologies, input datasets, and output archiving requirements so that model simulations and projections can be meaningfully compared to one another. The most important of these for our purposes is the CMIP. While Phases 1 and 2 of CMIP helped inform the IPCC Third Assessment Report (2001), it was really with the third phase, CMIP3, that the project fulfilled its potential. For the first time, CMIP3 provided a large multi-model ensemble of historic climate simulations and climate projections for the larger research community to analyze in depth.

CMIP Phase 5 is establishing a framework for the next five years of climate model intercomparison. It will provide standards for model runs performed in the next two years that will be analyzed in the IPCC Fifth Assessment Report (AR5) as well as guide projects that extend beyond the AR5 timeline. The AR5-related runs will have to be started this year in order to meet IPCC deadlines, so many decisions about model resolution and computer time allocations have already been made. Additional or augmented sets of model runs to better serve the needs of water utilities would likely have to wait until the core AR5 runs are completed.

CMIP5 will address decadal prediction with 30-year predictions (2005–2035), with most modeling centers planning to use AOGCMs for this purpose. In addition to the forecasts of the next several decades, these forecast models will be run retroactively to determine predictive skill. The intent is for each modeling center to produce ensembles of these predictions at as high a resolution as possible. For example, NCAR is planning to use 50-km resolution in the atmosphere for these decadal predictions, but a lower resolution model for the longer-term climate projections (Gerald Meehl, National Center for Atmospheric Research, personal communication, July 2009). Currently there are no plans that we are aware of to produce downscaled data from the decadal predictions for use in hydrology models, but producing statistically downscaled predictions would not be difficult to do after the fact, provided that skill of these predictions can be demonstrated.

Plans for projections out to the year 2100 and beyond allow both concentration-driven AOGCM and emissions-driven ESM projections. The emissions-driven projections and simulations require an ESM with a coupled carbon-cycle model, and these models are typically run at a lower resolution than the AOGCMs. To accommodate both these methods in a common analytical framework, the emission scenarios from the IPCC SRES (2001) used in CMIP3 (A2, A1B, B1) are replaced with representative concentration pathways (RCPs) that are consistent with a newer set of emission scenarios. These RCPs are labeled with numbers that correspond to the total radiative forcing from all anthropogenic (human-caused) factors in the year 2100 compared to pre-industrial values. These pathways also include land-use changes. The relationship between the RCPs and the underlying scenarios is described in Taylor et al. (2009).

Pathways RCP4.5 [4.5 watts per square meter (W/m^2) radiative forcing in 2100] and RCP8.5 (8.5 W/m^2) will be the first to be intensively modeled. To put this in context, a doubling of CO_2 over pre-industrial values yields 4 W/m^2 radiative forcing and a quadrupling yields 8 W/m^2. As with the set of SRES scenarios, the RCPs exhibit little divergence in CO_2 concentrations until after 2030. It is likely that the resulting climate change of these different pathways will not appreciably diverge until after mid-century, as was the case in CMIP3.

We identify three gaps in the current plans for CMIP5 runs that we find problematic from the standpoint of using well-tested methods to characterize regional climate change and uncertainties that we believe are needed for water resource applications. The first gap is the increasing reliance on ESMs for climate projections beyond a couple of decades, and it creates two problems. These models, though scientifically cutting-edge, are not as well tested as the traditional AOGCMs, and are typically run at lower resolutions. The indication is that roughly half the long-term climate projections in CMIP5 will come from ESMs and half from AOGCMs (Gerald Meehl, National Center for Atmospheric Research, personal communication, July 2009). The second gap is the insufficient number of ensemble members planned for the "Core" climate projections in CMIP5. As in CMIP3, this would lead to the inability to cleanly distinguish model-to-model differences in the climate signal from the model's natural variability. Finally, the higher-resolution models used for decadal prediction do not typically have a parallel set of climate projections for comparison. This report provides recommendations to address both of these deficiencies.

3.1.4 How are GCMs managed?

The development of GCMs is managed at over 15 modeling centers around the world (Meehl et al., 2007a, 2007b). Four of these centers are located in the United States (Table 3.1). Modeling centers exercise a large degree of organizational autonomy in developing climate models. However, some of the component models are developed in partnership with other institutions. The academic research community, through individual or collaborative scientific grants, plays an important role in developing new mechanistic process models and parameterizations. Even though the centers are organizationally autonomous, model development at each center does not occur in a scientific vacuum, as scientific ideas are constantly exchanged. As a result, the individual GCMs are not entirely independent of one another (Knutti, 2008).

Table 3.1. Major climate models and modeling centers in the United States participating in CMIP3 or CMIP5

Model	Institution	Web site/contact
Community Climate System Model (CCSM 4)	NCAR [funded by National Science Foundation and U.S. Department of Energy (DOE) Office of Biological and Environmental Research]	http://www.ccsm.ucar.edu Dr. Peter Gent gent@ucar.edu
Geophysical Fluid Dynamics Laboratory (GFDL) CM2.5, CM3 ESM 2.x	NOAA GFDL	http://www.gfdl.noaa.gov gfdl.climate.model.info@noaa.gov
GISS Model E	National Aeronautics and Space Administration (NASA)/GISS	http://www.giss.nasa.gov/tools/modelE/ Dr. Gavin Schmidt gschmidt@giss.nasa.gov
NASA GEOS5/AO (decadal only)	NASA/Goddard Space Flight Center	http://gmao.gsfc.nasa.gov/systems/geos5/ Dr. Max Suarez max.j.suarez@nasa.gov

Among modeling groups, the management of the NCAR Community Climate System Model (CCSM) stands apart from the others because it is based on a large community of scientists that extends beyond the lead institution and is governed by a diverse scientific steering committee.

3.1.5 How are climate projection intercomparison runs decided?

The CMIP5 intercomparison project will be the most significant set of GCM runs for the next 5–10 years for making comprehensive assessments of climate change and its impacts. These modeling efforts are coordinated by the Working Group on Coupled Models (WGCM, http://www.clivar.org/organization/wgcm/wgcm.php). The WGCM is part of CLIVAR (climate variability and predictability), an arm of the World Climate Research Programme (WCRP, http://wcrp.wmo.int/wcrp-index.html). It is up to the individual participating institutions to carry out the model development and perform the runs. Therefore, the CMIP5 standards often represent the least common denominator – institutions are free to exceed the recommendations. Decadal prediction efforts are organized by WGCM and coordinated through the WCRP Decadal Prediction Cross-Cut (http://www.clivar.org/organization/decadal/prediction.php). The US-CLIVAR Working Group on Decadal Prediction (http://www.usclivar.org/wgdp.php) will help facilitate the analysis of decadal prediction runs. More details of the CMIP process can be found in Meehl et al. (2007b).

3.1.6 How are the models evaluated for accuracy?

Weather prediction models are evaluated for accuracy by repeatedly comparing forecasts with what actually transpired. This is far more difficult to do with climate models because the models are used to project long-term climate trends, not short-term weather events. Climate models are evaluated on how well they can reproduce the climate of the present and the past by comparing the statistics of historical observations with those from a GCM's historical climate simulation. Often the comparison involves using gridded observational data, where nearby individual observing stations have been combined to form averages over grid cells that are of comparable scale to the GCM output.[4]

A simple statistical comparison of observations and model simulations is limited, in part, because we have imperfect information about the past climate. This is particularly true for the interior of the ocean, for sea ice, and even for many hydrologic quantities such as soil moisture. In addition, there is no guarantee that a good simulation of the past will result in an accurate prediction of the future because we may be getting the right answer for the wrong reasons. In practice we draw on multiple lines of evidence. Knutti (2008), for example, lists seven lines of

4. Therefore, it is not appropriate to attempt to analyze the skill of a GCM by comparing observed data from a single weather station in a grid box with the GCM's estimate of climate in that grid box.

evidence from which he gains confidence in climate model projections: "Models are based on physical principles; Models reproduce the mean state and variability in many variables; Models reproduce observed global trends in many variables; Models are tested on more distant past climate states; Multiple models agree on large scales; Projections from newer models are (broadly) consistent with projections from older models; We can understand the results in terms of simpler models and theoretical frameworks." We mention these here only to emphasize that model evaluation is more than simply a matter of statistical accuracy. A specific discussion of the ability to simulate past climate and trends is discussed below.

Over time, there will be increasing observations on the effect GHGs are having on the Earth's climate. Thus, as time goes on, there will be more information to use to assess models' performance in a changing climate.

3.1.7 Which processes are represented in the models?

Table 3.2 lists a typical breakdown of the main processes and parameterizations included in AOGCMs that are important for generating output relevant to water quality and quantity. As an example, the first row presents the convective parameterization, which computes the effect of the small-scale thunderstorms averaged over the grid cell. The convective precipitation it generates is particularly important for warm season precipitation totals and intense precipitation events. The heating of the atmosphere generated by convective precipitation is the main driver of the tropical atmospheric circulations that have global influence. Among the limitations include a poor simulation of the diurnal timing of precipitation (it tends to happen too early in the day), and the underestimation of intense rain events.

In reality, the processes listed in Table 3.2 are intricately connected, and models are evolving to a more unified view of parameterization. This list of parameterizations is not complete, as some processes of less relevance to water resources (such as gravity wave parameterization) are not included. ESMs include many additional processes (such as vegetation models, soil carbon processes, and surface ocean carbon uptake) that are not discussed here.

The strengths and limitations of the hydrologic processes in these models may be of particular interest to water utilities. GCMs typically include a hydrology submodel within their land surface component to account for the fate and transport of water (including solid and gas forms), but this output is rarely used directly for water resource applications. Typically, those studying climate change impacts on water resources use meteorological variables, such as temperature and precipitation, as inputs into hydrology models to estimate runoff (see Chapter 5). While the hydrology submodel in GCMs can be quite sophisticated in terms of the processes included, the large spatial scale of the model grid cell does not resolve critical hydrological phenomena, particularly in mountainous terrain. In addition, the climate biases of the GCM can also be

Table 3.2. Processes and parameterizations in AOGCM

Model process	What it does	Relevant model output	Strengths and limitations
Convective parameterization	Vertical movement of heat and moisture in thunderstorms. Convective precipitation. Provides critical input to cloud submodel.	Warm season precipitation, including monsoons. Cold frontal precipitation bands. Daily and hourly precipitation intensity in small regions. Upper tropospheric humidity (a determinant of global temperature). Heating of the atmosphere (main driver of the tropical circulation and Hadley Cells).	Timing of precipitation during day is poor in convective regions. Intense precipitation is underestimated. Does not model self-organized mesoscale systems such as squall lines, supercell thunderstorms, and large clusters of thunderstorms.
Boundary layer parameterization	Movement of heat, water vapor, and momentum (winds) away from the surface by turbulent motion in the lowest ~ 1 km of the atmosphere. Provides critical input to land surface models.	Surface air temperature; surface wind speed.	–
Radiative parameterizations	Calculates the absorption and scattering of shortwave (sunlight) and longwave (infrared or heat) radiative energy by air, humidity, clouds, and the land surface. Takes critical input from land surface and from cloud submodels.	Surface air and water temperature.	Performs well in clear-sky conditions. Uncertainties primarily due to clouds.
Cloud parameterizations	Models the distribution of cloud types and amounts within a grid cell and in the cloud parameterizations. Low-level (stratus and stratocumulus) clouds often handled separately in the boundary layer parameterization.	Surface air and water temperature. Critical factor in the global climate sensitivity. Low-level clouds.	Models have improved greatly. Most models now provide continuity in time for many properties. Cloud fraction can be poorly represented. Clouds remain a major source of uncertainty in climate models.

Table 3.2. Processes and parameterizations in AOGCM (cont.)

Model process	What it does	Relevant model output	Strengths and limitations
Dynamical core	Horizontal and vertical movement of heat, water vapor, and momentum at the scale of the model grid.	Seasonal cycle and annual temperature and precipitation. Atmospheric jet streams, frontal systems; extratropical cyclone formation and tracking. Hadley cells and subtropical high pressure (summertime circulation patterns, monsoons).	Winter storms (cyclones) well simulated.
Grid-scale precipitation	Precipitation due to grid-scale ascent of moist air.	Winter/spring precipitation.	Poor in mountainous regions due to coarse topography. Improves with higher resolution.
Land surface			
Biophysical processes	Evapotranspiration, movement of heat and moisture within the vegetation canopy.	Surface temperature; warm season precipitations (through evapotranspiration).	Vegetation response to climate change has many important uncertainties.
Surface hydrology	Surface hydrologic processes, including infiltration of water into soil, runoff. Deep groundwater poorly represented if at all in most models.	Surface temperature (through soil moisture). Critical determinant of evapotranspiration.	Some models track multiple soil/vegetation types within grid cell. Grid-average surface temperature problematic in heterogeneous/coastal regions.
River routing	Routes runoff at scale of grid cell.		Not considered useful due to large spatial scale and biases in inputs to hydrology.
Snow processes	Accumulation and melt of surface snowpack. Typically modeled very simply in GCMs.	Winter/spring temperature.	Smoother topography and large spatial scale poorly simulate evolution of snowpack. Melt due to dust-on-snow typically not included.

amplified by the nonlinearities in surface hydrology. One current practice to address this "scale" issue is to use bias-corrected[5] and downscaled climate model output as input to a higher spatial resolution watershed hydrology model that has been calibrated so that it reproduces historical conditions (e.g., runoff, snowpack) when forced by historically observed meteorology over the watershed. It should be noted that, while nominally the GCM's land surface model matches the grid of the GCM's atmosphere model, some land surface models break up coastal grid cells into land and ocean points, and can track multiple types of land cover within a grid cell in order to better calculate evapotranspiration and other variables.[6]

3.1.8 How well do the models reproduce past climate, variability, and extremes?

This section briefly summarizes how well the climate models in the CMIP3 archive simulate the mean climate, seasonal cycle, and observed trends of the 20th century, climate variability on interannual and decadal time scales, and extreme precipitation events.

The mean climate and seasonal cycles of surface air temperature are comparatively well reproduced:

- The large-scale spatial pattern of annual-average surface air temperature, including the contrast between maritime and continental temperatures, is well modeled (Solomon et al., 2007). The pattern correlation coefficient is 0.98, meaning that 95% of the large-scale spatial variance is captured. The pattern correlation is a measure of the similarity in the spatial variation of temperature after the global average temperature has been subtracted.

- The seasonal temperature cycle correlates with observations at 95% or better (CCSP 3.1) at large spatial scales.

- Seasonal (three-month average) model temperature biases[7] range from about −3°C to +1.5°C when averaged over the following IPCC-defined regions: western, central, and

5. The systematic differences between the observed climate record and a model's historical climate simulation is called the "climate bias" of the model. Various methods can be used to correct for these historical biases when producing projections of the future climate.

6. Lists of the parameterizations and submodels used in the individual CMIP3 models are detailed in Solomon et al. (2007, Chapter 8, Table 8.1), and more detail is available from the CMIP3 web site.

7. There is a difference between model estimates and observations. So a positive bias means a model is overestimating the value of a variable, e.g., a positive temperature bias means the model simulation is too warm or a positive precipitation bias means the model simulation has too much precipitation. Note that for the short period of comparison given in the IPCC report, 1980–1999, some of these "biases" could in fact reflect natural variability in temperature.

eastern North America (IPCC Chapter 11, Supp. Material; range over all seasons and over the 25th to 75th percentiles of model biases; these regions include the United States and the southern tier of Canada). The median biases among models go from a low of –2°C to a high of +0.4°C, depending on region and season.

- The diurnal temperature range (the difference of daily maximum and minimum temperatures) is generally less well simulated, with most CMIP3 models showing too small a diurnal range. Over the United States, these biases are largest in the West, with typical models showing 5°C too small a range (Solomon et al., 2007, Chapter 8, Supp. Material).

Precipitation is generally less well simulated than temperature:

- “[C]orrelation between models and observations is 50 to 60% for seasonal means on scales of a few hundred kilometers” (CCSP 3.1).
- Seasonal (three-month average) model biases in the mean precipitation climatology range from –25% to +25% over central and eastern North America, and from +21% to +103% over western North America (IPCC Chapter 11, Supp. Material; range over all seasons and over the 25th to 75th percentile of model biases). The median biases in western North America are particularly large, ranging from +28% (Summer) to +98% (Winter). Median biases in the other regions range between –16% and +21%.
- The average diurnal cycle in precipitation (e.g., the timing of thunderstorms) is very poorly modeled in many convective regions, including the central United States.
- Precipitation biases are generally largest in the Tropics. Because of teleconnections through the atmospheric circulation, this affects precipitation patterns around the globe, including over the United States.
- The North American monsoon, which is an important source of summer precipitation in the southwest United States, is generally not well simulated in the GCMs (Lin et al., 2008).

Studies that look at model performance for many variables at once yield some useful insights:

- Climate model simulations have generally improved since the early 1990s in their ability to simulate the mean climate and seasonal cycle (Reichler and Kim, 2008).
- Despite the increase in model performance over the last two decades, the range of global climate projections has not greatly narrowed. However, the understanding of these

ranges, the ability to distinguish among sources of uncertainty, and confidence in the stated range has improved (Solomon et al., 2007).

- The average across all models ("multi-model average") simulates current climatological averages better than any individual model (Gleckler et al., 2008; Reichler and Kim, 2008).

- For many risk assessment applications, it is better to use a range of individual models, rather than just a single model or the multi-model average, in order to sample a larger range of possible outcomes (e.g., Brekke et al., 2008).

- There is no "best" model. Individual models have different strengths and weaknesses that compensate for one another, so that most models fall within a relatively narrow range of overall skill (Gleckler et al., 2008).

- The relationship between model performance and reliability of projections of future changes on global and regional scales is not well understood (Knutti, 2008; Pincus et al., 2008).

- On a regional scale, culling or weighting models based on performance in simulating the regional climate does not necessarily yield a narrower range of projections (Brekke et al., 2008; Groves et al., 2008; Pierce et al., 2009). Some culling of models may be justified, however, if certain models fail to capture a regional climate phenomenon that is of interest, such as the North American Monsoon.

The ability to reproduce trends in the 20th-century climate is another indicator of confidence in the models. We focus on trends in global average temperature and in the pattern of regional temperature and precipitation changes over the United States:

- Global- and continental-average warming trends of the past century are well reproduced (Solomon et al., 2007; CCSP 3.1, 2008).

- The lack of observed warming during the 20th century in the southeastern and south-central United States is not reproduced in AOGCMs. The spatial pattern of precipitation trends is only broadly captured. Atmosphere GCMs that use the prescribed history of ocean temperatures do a much better job of reproducing these patterns, indicating that this discrepancy arises from the AOGCM simulation of ocean trends and variability (CCSP 3.1, 2008). It remains to be shown whether this discrepancy in the oceans represent a systematic problem in the GCMs or simply is due to the "free running" GCMs not capturing the observed phasing of natural variability.

- While the models are broadly consistent with the observed trends over the 20th century, this consistency is not strong enough, and the observed trends are still too small to use them to narrow the range of climate projections (Knutti, 2008).

Climate variability and extremes can be influential factors for water utility planning. It is important for water utilities to have information on critical dry and wet periods – droughts and floods – to determine system performance. The ability of GCMs to simulate climate variability depends on the phenomenon in question:

- GCMs generally underestimate the occurrence of heavy precipitation. Because many of these events have a small spatial extent, the simulation of these events is severely limited by the grid spacing and the timestep of the model. Simulation improves with higher resolution (Iorio et al., 2004, referenced in CCSP 3.1, 2008).

- The wintertime storm track variability, as measured by upper-level winds in the atmosphere, is generally well represented in the climate models with resolution of 200–300 km or better. The amount of precipitation delivered by these storms is not as well simulated in mountainous regions, due in part to the smoother topography of the GCMs.

- Most GCMs produce variations in the tropical Pacific that have some characteristics of the observed ENSO variations. Most GCMs have significant errors in the amplitude or frequency of ENSO, and most have errors in the seasonal timing of ENSO. ENSO is an important determinant of the sequence of wet and dry years in the western and central United States. Models that may have a good ENSO simulation in one version (the Hadley Centre HadCM3 model) may have a poorer simulation in a subsequent release (HadGEM1). Therefore, we agree with the statement that “realistic simulation of El Niño and its global influence remains a challenge for coupled models” (CCSP 3.1, 2008).

- Most GCMs produce variations on multi-decadal time scales in the Atlantic and Pacific, but it is difficult to evaluate how close these are to the observed record due to the small number of decadal events in the record. All GCMs underestimate decadal variation in the Tropical Pacific that are thought to be an important source of the PDO (CCSP 3.1, 2008; Solomon et al., 2007, Chapter 8).

- Models exhibit “much weaker decadal variability” in North American precipitation than observed (CCSP 3.1, 2008).

More detail on the evaluation of climate model skill is discussed in Chapter 8, “Climate Models and their Evaluation,” and Chapter 11, “Regional Climate Projections,” of the AR4 (Christensen et al., 2007), and in the U.S. Climate Change Science Program SAP 3.1, “Climate Models: An Assessment of Strengths and Limitations” (CCSP 3.1, 2008). Finally, we note that these models are generally “tuned” (calibrated to observations) on only a few, very general measures such as the globally averaged top-of-the-atmosphere energy balance. We have focused above on variables that are not tuned.

3.1.9 How do models differentiate between anthropogenic climate trends and climate variability?

Anthropogenic climate trends in the historical record are differentiated from natural climate variability through *detection and attribution* methods that combine the observed climate record with model simulations. If the observed trends are consistent with the climate model historical simulations (including historical GHG concentrations), but inconsistent with a parallel set of model simulations where GHGs have been kept at pre-industrial levels, then these trends are attributed (in part) to emissions of GHGs. The attribution of global-average temperature to GHG emissions is more difficult at smaller spatial scales because natural variability is larger at these scales. Attribution of precipitation changes is also difficult because of large variability. *Fingerprinting* techniques are sometimes used to choose distinctive spatial patterns, rather than simple area averages to aid in attribution.

By and large, these techniques have been used to determine the likelihood that an observed climate change is of human origin (e.g., Stott et al., 2003), or to help constrain the global temperature signal (Stott et al., 2006), but not to determine the magnitude of the human-caused climate signal on continental and regional scales. It is not currently possible to use the observed trends to significantly narrow the range of plausible climate projections beyond what is stated in Solomon et al. (2007). However, as the climate change signal increases in magnitude on both global and regional scales, more advanced techniques that combine models and observed data will eventually provide a powerful tool to reduce uncertainty in climate projections. The timeframe over which this improvement may occur depends, among other factors, on the rate at which the regional climate change “signal” rises above the variability.

For climate projections, averaging over a large (> 10 members) ensemble of runs from a single model that start with different initial conditions (see Section 3.1.8) is the most accurate method of separating the time-evolving climate change signal in modeled variable from the internal (i.e., unforced) variability. A much larger ensemble (> 30 members) is needed to determine trends in variability, such as changes in standard deviations and ENSO frequency and magnitude. The CMIP3 model archive was deficient in this regard, with many models represented by only a single run. Therefore, it was difficult to accurately separate the climate change signal from the internal model variability for a given model. This can be a particularly large problem over the mid-21st century planning horizons of many water utilities, where the climate change signal is not as large as later in the century. Approximate techniques, such as pattern scaling (e.g., Mitchell et al., 1999), can be used. In pattern scaling, a single spatial pattern over the globe is used to represent change for a variable such as precipitation over the 20th and 21st centuries. Only the amplitude of this pattern (a single coefficient, e.g., how much of an increase or decrease in precipitation) is allowed to vary in time. The spatial pattern and time-varying amplitude are determined from a GCM run. In effect this procedure rescales the large changes that are projected for the end of the 21st century in order to estimate the near-term changes. Pattern scaling is thought to be more appropriate for temperature trends than for precipitation Nonetheless, we think that a more complete set of GCM ensembles would be a beneficial addition to the plans for CMIP5.

3.1.10 What are the main sources of uncertainty in the GCM climate projections?

Uncertainty in climate projections can be divided into three categories: climate driver uncertainty, climate system uncertainty, and downscaling uncertainty. Future GHG emissions and other anthropogenic drivers of climate change depend on socioeconomic, demographic, and technological factors, as well as carbon mitigation policy. In addition, there are other unpredictable climate drivers, such as the occurrence of volcanic eruptions and long-term variations in solar output. These latter two uncertainties, however, are not new, and their effects are included in the historical and paleoclimate records of climate variability. Improved climate modeling cannot narrow these uncertainties. Thus, a wide range of plausible future conditions can make adaptation more challenging. Uncertainties in socioeconomic climate drivers becomes more significant in the latter half of the 21st century and beyond, but uncertainties in volcanic and solar forcing can have large impacts in the near-term as well.

Climate system uncertainty can be split into three parts: uncertainty in the carbon cycle (and other processes) that translate the climate drivers into GHG concentrations, uncertainty in the climate response to those GHG concentrations (and to other climate drivers), and uncertainty due to internal (“natural,” or “unforced”) variability. Some discussions include the determination of radiative forcing due to these climate drivers as an additional source of uncertainty, but for this discussion we treat radiative uncertainties as part of the climate response. Climate system uncertainty is a fundamental characteristic of the complex, nonlinear dynamics of the climate system. The carbon cycle is included in ESMs, and as with the climate drivers themselves, the uncertainties in the carbon cycle become more significant in the latter half of the 21st century and beyond.

The climate response to increasing GHG concentrations can be modeled using AOGCMs without an interactive carbon cycle. Even given the same projected values of GHG concentrations, different AOGCMs produce different magnitudes and patterns of climate change. These differences arise from both structural differences among the models (different classes of parameterization, for example) or from the choice of parameter values in a given model. The impact of structural differences among models can be investigated by comparing model projections from many different modeling centers, a so-called multi-model ensemble. The effects of different parameter choices for a single model can be investigated through a "perturbed physics ensemble" of experiments such as the effort of climateprediction.net (Stainforth et al., 2005). Perturbed physics ensembles examine massive sets of runs from a single medium-resolution climate model with different model parameter choices (but the same model structure).

An individual model tends to produce a dominant regional pattern of anthropogenic change that increases over the next century (Solomon et al., 2007, Chapter 8, Supp. Material). However, these regional patterns differ from model to model. The focus of this report is on improving climate modeling to increase understanding of climate system uncertainty and reduce it where possible, including seeking a convergence in the regional patterns of climate change among models.

As noted above, climate variability is also a factor in the range of climate model output and must be taken into account when estimating the climate change signal. The simulated climate over several decades may be quite different given slightly different initial climate conditions in the model (analogous to the "butterfly effect" in weather forecasts). In addition, the GCM projections are not started with the observed conditions, which must be taken into account when using climate model projections. Sufficiently large ensembles of model runs can distinguish climate change signal from model-simulated natural variability. Climate variability is particularly important in the near term, and for highly variable quantities, such as precipitation. But climate variability of the sort described here – the fact that climatological averages over different 30-year periods are not the same, for example – would be a source of uncertainty about the future even in the absence of human-caused climate change. Downscaling uncertainty is discussed in Section 3.2.2.

Comprehensive models being developed are attempting to model the combined effects of all these uncertainties in order to produce a fully probabilistic projection of climate change (Sokolov et al., 2009). These models are in their infancy, and use highly simplified models of the climate system. They have focused on projections of the global average temperature, and do not yet adequately treat regional climate change.

As noted in Section 3.1.6, despite the increase in model performance over the last two decades, the range of global climate projections has not greatly narrowed. However the understanding of these ranges, the ability to distinguish among sources of uncertainty, and confidence in the stated range has improved (Solomon et al., 2007). However, what is meant by "uncertainty range" has changed over time from a qualitative statement in the earlier IPCC assessments to a quantitative statement in the Fourth Assessment Report.

The IPCC concluded that the there is at least a two-thirds probability that the equilibrium climate sensitivity (defined as the response to doubling CO_2 when the model is run to long-term equilibrium) will fall between 2 and 4.5°C. (Note that this is based on more information than just the range of GCM projections.) Roe and Baker (2007), among others, see little hope for substantially reducing this range through model improvement within several decades. However, if climate sensitivity is on the high end of the range, it is unlikely to make a substantial difference in realized temperatures in the 21st century (for more information, see Solomon et al., 2007, Table SPM.3; and Meehl et al., 2007a, Figure 10.29).

The quantification of uncertainty for regional and local climate change is more difficult, and less developed than for global change. Whether or not the GCM range underestimates regional uncertainty depends on the variable considered and method used. However, it is known that many sources of regional uncertainty are not included in the GCMs, including regional land surface changes (Solomon et al., 2007, Section 11.10).

3.1.11 How are large sets or subsets of model runs chosen, evaluated, and used?

The CMIP3 archive presents us with over 100 model projections out to the year 2100.

Solomon et al. (2007) did not differentiate among these models according to any measure of skill. The choice and use of model projections should serve the purposes of the climate impacts or vulnerability study it is supporting. For example, the choice of projections may differ, depending on whether one is conducting a probabilistic risk assessment or a scenario-based planning exercise.

In most cases, this dictates looking at a range of projections, but which range is best to use? Some analysts have tried to evaluate the models (e.g., Wigley, 2008), or use their skill in weighting the different model projections (e.g., Brekke et al., 2008; Tebaldi and Lobell, 2008), or provide a probability distribution of projections for input into impacts models (e.g., Groves et al., 2008). Another method is to choose a small sample of runs that spans the range of model projections in a particular region. This latter course may be necessary if the cost of exploring the impacts or adaptation strategies for each projection is large. The IPCC guidelines on the development of regional scenarios from GCM projections can be found in Mearns et al. (2003), Wilby et al. (2004), and IPCC-TGICA (2007).

The future holds new challenges in the choice of model output. The avalanche of model output that will be available with CMIP5 poses not only a technical challenge, but a conceptual challenge as well. How should we deal with the mixture of concentration-forced AOGCM and emissions-forced ESM runs at very different resolutions? Should decadal predictions be combined with climate projections, and if so, how?

3.1.12 How can a model's predictive capability be improved?

The following ways of improving on the state of the art of the climate models themselves have been identified (U.S. DOE, 2004):

- Increase the spatial resolution of the grids of the coupled model components
- Increase the completeness of the coupled model by including interactive component models, such as chemistry and vegetation models
- Increase the fidelity of the model by improving parameterizations and process models
- Increase the length of both control and climate-change scenario runs
- Increase the number of simulations in each ensemble of control runs or climate-change-scenario runs
- Increase the number of climate-change scenarios.

To these we add:

- Develop systematic methods for model improvement, and in particular, advanced methods for using the observed record to constrain model parameters.

In this report we focus on spatial resolution, model parameterizations, ensembles of model runs, and using data to better constrain models. The models in the current generation are projected far enough into the future to be useful for water utilities' planning horizons so little utility is gained by longer runs (e.g., into the 22nd century or beyond). The component models are also complete enough for this purpose.

Due to the complexity of these models, there is currently no systematic methodology for their improvement. It is not a simple matter of calibration. In practice, improvement in a particular parameterization happens through what might be called "expert-guided trial and error" – that is, the expert judgment of a team of scientists based on theoretical and conceptual models and intuition, and on insights from data analysis. Deficiencies in parameterization or in the climate statistics of the model are identified, and likely model improvements are repeatedly tested in the GCM code to see whether the deficiencies are ameliorated. It is difficult to foresee all the implications of a model change. Improvement in the simulation of one variable, one geographic area, or one time scale may be offset by deterioration in another, so the process can be tedious and difficult. (This can be a typical problem in modeling many different complex systems.)

Parameterization development is mostly conducted by small research groups working at modeling centers and universities. As a result, progress is usually in small increments. The cycle of IPCC assessments has strongly influenced the tempo of model improvements, with the typical cycle between model versions being about six years. Major model improvements, such as introducing new classes of parameterizations and new component models, take on the order of a decade or more.

Changes and improvements in parameterizations and in the development of component models in general are limited by the number of skilled scientists working on the problem, by the organizational structures that coordinate this research, and by access to adequate computational resources. Climate Process Teams in the United States (U.S. CLIVAR Office, 2008) is one approach for increasing the effectiveness with which improvements in the science results in improvements in modeling. This approach funds research teams that include theoretical, observational, and modeling experts to guide new ideas from concept to implementation. We believe that the increasing scale and complexity of model development will favor such collaborative efforts in the future.

Because of the difficulty and lack of certainty regarding improving GCM parameterizations, we do not recommend a major additional investment in that area to reduce modeling uncertainty. That is, we could not identify any specific GCM parameterization improvements that, by themselves, would address the four dimensions of model improvement identified in Chapter 1. However, in Chapter 4 we recommend improving certain parameterizations and process models for RCMs, and these will eventually feed into the development of high-resolution GCMs and help to address the mismatch of spatial scale between climate models and water resource models.

Funding can affect GCM development on several fronts. The most important is the investment in the scientists and engineers who develop and improve the models and analyze the model output. Funding to support and retain the top scientists at universities and federal laboratories, and investment in graduate and postdoctoral education are essential. Focused scientific research programs can bring together the observational, modeling, and analysis needed to tackle the difficult problems involved in model improvement. Some areas that warrant special attention by water utilities in North America include the improved use of observations to develop models, the development of advanced techniques to combine observations, and models to narrow the range of climate projections. In addition, a concerted effort to increase scientific understanding of and ability to model the Tropical Pacific would likely help to reduce the uncertainty in precipitation projections over much of North America. The CMIP3 models show significant disagreement on climate change in this area, which has a strong influence on the climate of North America.

3.1.13 The costs and benefits of increasing model resolution

The first rule about higher resolution is that it is computationally expensive. Doubling a model's resolution increases the computations by about 16 times (roughly a factor of two for each spatial dimension and another factor of two for the smaller timestep). In order to evaluate the necessary resources that should be put into increasing model resolution, it helps to have an understanding of which new features of the climate and which new processes will be resolved with higher and higher resolution. The approximate spatial scale needed to resolve selected climate phenomena related to precipitation and temperature is summarized in Table 3.3. A similar table for ocean phenomena is presented in Appendix E. The CMIP3 models, which have a resolution of 100–400 km, have high enough resolution to reproduce the large-scale features of the Earth's climate, including the atmospheric jet streams, winter storms and the average wintertime storm tracks, and the Hadley cells that influence the subtropical deserts, as well as many of the major ocean current systems. The ability to model these and other large-scale climate phenomena has led to an increase of confidence in the model climate projections, including confidence in the projections that the northern mid-latitudes will get wetter and the subtropical arid regions drier. As resolution of the atmosphere is increased to the 50–100 km range, the gains are primarily in the resolution of topographic and coastal effects. There is some evidence, however, that the mean tropical climate of the NCAR CCSM may be significantly improved at 50-km resolution, with precipitation bias over the United States also reduced (but still too wet in the West) (Gent et al., 2009).

Table 3.3. Approximate climate model spatial resolution needed to simulate climate phenomena related to precipitation and temperature. These were selected to illustrate the main benefits of different resolutions across scales relevant to both GCMs and RCMs.

Model horizontal resolution	Simulated phenomenon	Importance to climate and water resources
Atmosphere model		
500–50 km	Hadley cell; subtropical high pressure; intertropical convergence zone; monsoons.	Dominant structures of Tropical and Subtropical climate, including southwest United States arid regions; heat waves.
	Midlatitude jet stream, surface westerlies and cyclonic storms.	Dominant structures of midlatitude climate. Cold-season precipitation and temperature; global movement of heat and moisture; continental vs. maritime climates; cold air outbreaks.
250–50 km	Large-scale coupled (atmosphere/ocean) convective systems (Tropics).	Tropical variability, e.g., ENSO, and its global effects, including temperature and precipitation over much of the United States.

Table 3.3. Approximate climate model spatial resolution needed to simulate climate phenomena related to precipitation and temperature (cont.). These were selected to illustrate the main benefits of different resolutions across scales relevant to both GCMs and RCMs.

Model horizontal resolution	Simulated phenomenon	Importance to climate and water resources
50–4 km	Organized convective "mesoscale" systems (midlatitudes).	Great Plains and eastern United States summer precipitation; extreme precipitation events; cloudiness; diurnal timing of precipitation.
	Topographic effects (depends on scale of topography).	Snow vs. rain in mountains; extreme winter precipitation (coastal mountains); rain shadows; windstorms; winter storm formation in lee of Rockies.
4 to < 1 km	Individual convective clouds "cloud resolving" No need for convective parameterization.	All aspects of tropical and midlatitude precipitation.
	Low-level clouds (stratus/stratocumulus).	Reduced uncertainty in cloud effects on global climate sensitivity; surface temperature at "observing station" scale.
	Surface hydrology; small basin river routing and reservoirs	Directly simulates surface hydrology at finest scales of interest to water utilities.

Increasing GCM resolution eventually raises the question of whether is it possible to run GCMs at high enough resolution so that downscaling is no longer necessary. Plans for many CMIP5 climate projections are tentatively in the 100–200 km range, while some current GCMs are approaching the 50-km resolution. Getting beyond this in the current generation of models will be difficult. For example, increasing resolution in the atmosphere from 100 km to 12 km would require approximately a 5,000-fold increase in computer power. In addition, we believe that relatively few modeling centers will be able to run models at resolutions < 100 km, so in order to sample an adequately broad range of global models (i.e., to have a large enough multi-model ensemble) will require downscaling those models in the CMIP5 archive with coarser resolution.

The next major milestone that is sought in climate modeling is the ability to simulate the atmosphere at grid cell sizes of < 4 km. This resolution is considered to be "cloud resolving," so that the convective parameterization would no longer be needed, though to resolve clouds well probably requires grid cells less than 1 km on a side. In the ocean, the analogous effort is to create so-called "eddy-resolving" models with a resolution of less than 10 km globally, and this effort is further along in its development. There are two challenges in getting resolution this high. The first is in developing the numerical methods and parameterizations that work at these ultra-high resolutions. The second is in developing computers powerful enough to run the thousands of years of simulations needed for climate research. Both are active areas of research, but the development of coupled models at this resolution is in its infancy. While it is hoped that going to this resolution will reduce the range of model projections, it is not at all certain that this will be the case. There are, for example, other sources of uncertainty in the climate models besides the convective parameterization. At any rate, the ability to run such models globally for routine weather forecasts is probably a decade into the future, with the timetable for climate projections at this scale uncertain (Randall and Arakawa, 2009).

We do not recommend investing all resources in higher resolution at the expense of other efforts. The practical question with the current dynamical models comes down to whether it is better to support a small number of 50-km global model runs or many more runs at 100-km resolution or larger, with some of these runs downscaled to 10–20 km using an RCM. In our view, it makes sense to support global 50-km GCM runs only if they can be shown to significantly improve the simulation of the large-scale climate features, especially in the Tropics, and thus give better input for both dynamical and statistical downscaling methods. Otherwise, the resources are probably better spent on characterizing the uncertainties through larger ensembles, and on achieving much higher resolution through statistical and dynamical downscaling of these lower-resolution GCM runs.

3.1.14 Are the most powerful computers available today being utilized by these models?

Globally, the fastest supercomputers have increased their power by a factor of 10 every four years and are projected to do so well into the next decade (Top500.org, 2009). Such computing power is achieved by increasing the number of processors in a massively parallel computer, although the use of "accelerators" based on computer graphics cards and other innovative computer architecture shows promise to boost computing capabilities (U.S. DOE, 2004).

The most powerful supercomputers on the most recent Top500.org list (November 2008) are run by the DOE's National Nuclear Security Administration (NNSA). Currently, the U.S. modeling centers do not have sufficient in-house computer power to perform climate simulations and projections at the desired resolutions. However, these climate models share time with other applications on some of DOE's fastest machines. Two efforts in particular are the DOE/NCAR CCSM Consortium effort and the DOE/NOAA Coupled High-resolution Modeling of the Earth System (ChiMeS) project. The recent allocation of $170 million to NOAA for climate model computing in the American Recovery and Reinvestment Act of 2009 and the development of a petascale computing center for the geosciences (peta = 10^{12} petaflops and petabytes refer to the computing power and data storage) to be run by NCAR and the University of Wyoming will help diversify these resources. Given these recent improvements in supercomputer resources, the prospect is good for a comprehensive set of GCM projections at better than 50-km resolution within a decade. However, dedicated computer resources and data archives to support dynamical and statistical downscaling for regional applications, including water resources, would be beneficial in the near term.

3.2 Climate Model Downscaling

This section provides an overview of downscaling techniques, where uncertainties arise in these methods, and how uncertainty may be more effectively quantified and communicated for regional and local projections of relevance to water utilities.

3.2.1 What are GCM downscaling techniques?

GCM downscaling techniques are methods that transform output from GCM projections into regional and local projections containing much more spatial and temporal detail that may be useful for water utilities. Essentially, GCM downscaling techniques aim to simulate the behavior of local climate processes that are absent in GCMs. This might mean, for example, transforming the broad wind patterns of storms embedded within the jet stream by adding the effects of mountainous terrain to create local variations in wind patterns.

Downscaling techniques are grouped into two classes: statistical and dynamical. Statistical models use empirical relationships between large-scale and local climate conditions. They have as their foundation the principles of stochastic and statistical models, and employ techniques such as optimal data fitting, regression, and Bayesian inference. They use extensive datasets of observations and GCM output to identify robust associations between large-scale and local climate conditions. These statistical associations are then used to produce local climate projections when provided data from a GCM projection.

Dynamical downscaling models are based upon mechanistic relationships such as energy and mass conservation, just as are GCMs. They are called “dynamical” by analogy with Newtonian Physics where a force produces a response at some later time. That is, the time evolution of “dynamics” of the system is predicted through the mechanistic relationships. Dynamical models develop local climate projections when provided GCM projections by simulating local mechanistic climate processes, such as sea breezes and mountain-forced circulations, that are absent from GCM simulations. Because of their focus on regional climate mechanisms, they are often called regional climate models. It should be noted, however, that some statistical models also include time-evolving (i.e., dynamic) relationships. Thus, the following sections emphasize the empirical versus mechanistic nature of these techniques when making distinctions in their application for downscaling.

There are several commonalities in the way statistical and dynamical downscaling techniques are used. For example, they both rely upon skillful representation by GCMs of large-scale climate conditions, such as the position of the jet stream. For this reason, the following sections first describe the aspects that are common to all downscaling techniques before delving into their peculiarities.

3.2.2 What uncertainties are associated with climate model downscaling?

Downscaling techniques add a layer of modeling in-between GCM projections and application of projections in water utility management strategies. This adds some level of uncertainty in regional climate change projections, the nature of which is described below. A number of water utilities have expressed concern that the uncertainty implied by the range of downscaled GCM climate change projections is too large to drive decisions on strategic capital investments (see Items 1 and 2 in Chapter 1, Section 1.1). The overview provided below points to the need for a coordinated effort to better communicate to water utilities the degrees of uncertainty that exist and how they arise from various sources, so that they may make best use of regional climate projections in accordance with their management strategy. The need for this is succinctly stated in the U.S. Climate Change Science Program Scientific Assessment Report 5.1:

> For decision-makers, a critical issue concerns the extent to which the various scenarios reflect the actual uncertainty of the relevant risks versus the uncertainty due to methodological approaches and biases in underlying models.

The review of climate change studies undertaken by water utilities reported earlier in this document indicates that little attention has been given to communicating all sources of uncertainty in regional climate projections. This disconnect in communicating uncertainty can arise for many reasons but, in our opinion, the most fundamental reasons are the following:

1. Climate researchers and water utility planners have vastly different definitions of, and tolerances for, uncertainty. These differences may not have been explicitly recognized.

2. Climate scenarios are provided to water utility planners in an ad hoc manner rather than as a dataset carefully designed to explicitly address their needs. As a result, management approaches for addressing uncertainty cannot be applied effectively using the current sets of climate projections.

Even with improvements in climate models, it is very likely that substantial uncertainty about future climate change at scales water utilities require to properly model their systems will remain. Therefore, it is necessary not only to improve climate models but, just as importantly, to develop methods by which uncertainty can be more completely articulated and thereby address the concerns that water utilities have expressed regarding uncertainty in regional climate projections (see Chapter 5 and the Means et al., 2009 report).

As discussed in Section 3.1.8, uncertainty in climate projections can be divided into three categories: climate driver uncertainty, climate system uncertainty (including variability), and downscaling uncertainty. Downscaling uncertainty is introduced by the inconsistency between the climate conditions as simulated by the GCM and by the downscaling technique. This inconsistency is inherent in all forms of downscaling, whether dynamical or statistical. To illustrate the concept of inconsistency, consider the following “though experiment”: Suppose a GCM were constructed with a resolution fine enough to directly simulate climate system variability at the spatial and temporal scales of station observations, say, 100 meters or less. Also, suppose the same GCM is used but with coarser resolution, say 100 km, and downscaling is applied. These two approaches would not produce the same climate statistics at the spatial and temporal scales of station observations. That is, the downscaling technique would produce local climate statistics different from what the high-resolution GCM would produce. (Of course, both methods may differ from reality.)

Even when adding downscaling uncertainty into the climate simulation, downscaling techniques provide useful representations of climate system uncertainty over a range of spatial and temporal scales: from sub-continental regions such as the Pacific Northwest to individual observing stations, and for daily and even sub-daily periods. Downscaling techniques have the additional benefit that they consider local and regional climate drivers, such as urban expansion and other changes to the landscape, that may affect temperature and runoff trends, and that would be missing from GCM projections.

3.2.3 How do GCM downscaling techniques affect the quality of climate scenarios?

Three aspects of GCM downscaling techniques affect the quality of downscaled climate scenarios available for water utility planning:

1. *Downscaling input data.* The phrase “garbage in garbage out” applies to downscaling. Downscaling will not correct large-scale errors, such as errors in the connection between Tropical ocean temperatures and the position of the mid-latitude jet stream, from the GCMs. The quality of large-scale data from GCMs must be good. Any improvements to GCM climate and variability, therefore, necessarily improve the end result from downscaling.

2. *Downscaling model.* The model adds small-scale information to the input GCM data that is inconsistent with what the GCM would provide if it had sufficient spatial/temporal resolution. The structure of the model determines the plausibility, accuracy, and precision of the downscaled data. Equally important is the quality of observational data needed for validation and calibration of downscaling models.

3. *Downscaling output data.* The output data must appropriately translate the quality of large-scale data from the GCM to variables of interest at sufficient spatial/temporal resolution for water utilities.

3.2.4 How are downscaling techniques developed and managed?

Development of downscaling techniques goes through cycles that are loosely connected to CMIP experiments (see Section 3.1.3). However, the overarching administration of CMIP does not contain explicit plans for providing data for downscaling activities, and in the past few institutions that produce GCM projections ensure their archives will be sufficient for downscaling techniques.

Downscaling techniques are primarily developed in the United States through short-term projects funded by grant programs. In fact, there are only four long-standing climate dynamical downscaling programs supported at government research institutions in the United States. Groups that specialize in statistical downscaling are even more rare in government-sponsored facilities and are difficult for the author to identify at academic institutions since they do not typically reside in academic departments with a climate modeling focus but instead are located in a wide variety of academic departments with research focused on a particular impact of climate change. (Table 3.4 presents information on climate downscaling groups at government-sponsored facilities, while Table 3.5 presents information on institutions that have developed climate downscaling methods.) The emphasis on development of downscaling techniques within the context of projects funded by grant programs has resulted in evaluation and development of downscaling techniques that are specific to the goals of scientific projects, rather than user community needs.

Table 3.4. Climate downscaling groups at government-supported facilities with long-standing financial and infrastructure support

RCM/method	Institution	Web site	Contact
MM5, WRF	Pacific Northwest National Laboratory	http://www.pnl.gov/atmospheric/research/regional.stm	Dr. Ruby Leung, PNNL PO Box 999 MSIN: K9-24 Richland, WA 99352 509-372-6182 ruby.leung@pnl.gov
NRCM	NCAR Mesoscale and Micrometeorology Division	http://www.mmm.ucar.edu/modeling/nrcm/index.php	Dr. Bill Kuo MMM/NCAR PO Box 3000 Boulder, CO 80307-3000 303-497-8910 kuo@ucar.edu
C-FDDA	NCAR, Research Applications Laboratory, National Security Applications Program	http://www.ral.ucar.edu/nsap/themes/climate.php	Scott Swerdlin RAL/NCAR PO Box 3000 Boulder, CO 80307-3000 303-497-8378 swerdlin@ucar.edu

Table 3.4. Climate downscaling groups at government-supported facilities with long-standing financial and infrastructure support (cont.)

RCM/method	Institution	Web site	Contact
Climate MM5, Climate WRF	Illinois State Water Survey, Center for Atmospheric Science, Climate, Air Quality, and Impact Modeling System	http://www.isws.illinois.edu/atmos/modeling/caqims/	Dr. Xin-Zhong Liang Illinois State Water Survey 2204 Griffith Dr. Champaign, IL 61820-7495 217-244-6864 xliang@illinois.edu
Various statistical and stochastic methods	NCAR, Research Applications Laboratory, Integrated Science Program	http://www.isp.ucar.edu/	Dr. Peter Backlund Director, NCAR/ISP PO Box 3000 Boulder, CO 80307-3000 303-497-1103 backlund@ucar.edu

C-FDDA = Climate-Four Dimensional Data Assimilation; MM5 = Penn State-National Center for Atmospheric Research Mesoscale Model version 5; NRCM = Nested Regional Climate Model; WRF = Weather Research and Forecasting.

Table 3.5. Institutions that have generated downscaled climate simulations

Technique, name	Institution	Contact
RCM: RSM-NCEP	NOAA National Centers for Environmental Prediction	Hann-Ming Henry Juang Henry.Juang@noaa.gov
RCM: RSM-ECPC	UC San Diego, Scripps Oceanographic Institute, Experimental Climate Prediction Center	Masao Kanamitsu mkanamitsu@ucsd.edu
RCM: WRF-ARW, MM5	Pacific Northwest National Laboratory	Ruby Leung Ruby.Leung@pnl.gov
RCM: WRF-NMM	Iowa State University	Chris Anderson cjames@iastate.edu
RCM: MM5	Iowa State University	Ray Arritt rwarritt@bruce.agron.iastate.edu
RCM: Climate WRF	Illinois State Water Survey	Xin-Zhong Liang xliang@illinois.edu
RCM: ETA-NCEP	NOAA National Centers for Environmental Prediction	Rongqian Yang Rongqian.yang@noaa.gov
RCM: ETA-SIB	UCLA	Yongkang Xue yxue@geog.ucla.edu
RCM: RAMS	Colorado State University	Lixin Lu lixin@atmos.colostate.edu
RCM: RegCM3	UC Santa Cruz	Mark Snyder msnyder@pmc.ucsc.edu

Table 3.5. Institutions that have generated downscaled climate simulations (cont.)

Technique, name	Institution	Contact
RCM: RAMS, WRF	University of Arizona	Christopher Castro castro@atmo.arizona.edu
SD: LLNL-Reclamation-SCU WCRP CMIP3	Lawrence Livermore National Laboratory, Bureau of Reclamation, Santa Clara University	Edwin Maurer EMaurer@scu.edu
SD: U. Washington Climate Impacts Group	University of Washington	Many investigators
SD: Indiana University Precipitation Climates	Indiana University	Sara Pryor spryor@indiana.edu

ETA = ETA Coordinate Mesoscale Model; MM5 = Penn State-National Center for Atmospheric Research Mesoscale Model version 5; RCM = regional climate model; RAMS = Regional Atmospheric Modeling System; RegCM3 = Regional Climate Model version 3; RSM = Regional Spectral Model; SD = Statistical Downscaling; WRF = Weather Research and Forecast Model.

Indeed, the North American Regional Climate Change Assessment Project (NARCCAP, http://narccap.ucar.edu/) represents the most ambitious attempt to quantify uncertainty in regional climate projections. It will contain results from six RCMs that each are provided data from two of four participating GCM institutions that each submitted a single GCM projection from a single emissions scenario.

3.2.5 What framework is applied for analyzing errors in downscaling techniques?

A framework that allows for analysis of errors in statistical and dynamical downscaling techniques is described below (it is assumed that all analyses are performed on identical time scales, e.g., daily, monthly, or annual).

1. *Baseline climate simulation.* The downscaling technique is calibrated on the target region for the target variables by using observations or a proxy for observations from the recent past as input. The accuracy of the calibration is checked by simulation of an independent period. Evaluation of the baseline climate simulation provides a measure of the error introduced by the downscaling technique.

2. *Alternative baseline climate simulation.* The downscaling technique is applied without recalibration to another region or another period within the same region in which the climate conditions are quite different and may have characteristics expected under climate change within the target region. The differences between this simulation and the baseline climate simulation provide a measure of how robust the downscaling technique is to changing climate conditions.

3. *Historic climate simulation.* The downscaling technique is provided data from a GCM historic climate simulation. The differences between this and the baseline climate simulation provide a measure of the errors introduced by the inherent inconsistency of climate conditions between downscaling techniques and GCMs, the skill of the GCM at representing large-scale climate conditions, and the possibility that slowly varying ocean conditions in the GCM and observations are out of phase.

4. *Future climate projection.* The downscaling technique is provided data from a GCM future climate projection. The differences between this and the historic climate simulation is a measure of the climate change signal, i.e., how much change is projected due to increased GHG concentrations.[8]

3.2.6 What types of climate model downscaling techniques have been developed, and what are their strengths and weaknesses?

Climate model downscaling techniques involve three types of models: statistical downscaling models, RCMs (a form of dynamical downscaling), and time-slice general circulation models (also a form of dynamical downscaling).

Statistical downscaling models

Statistical downscaling models use empirical mathematical relationships between output from GCM simulations of historic climate and local climate observations (Figure 3.3). Alternatively, or additionally, these relationships can be developed from observations that have been aggregated to the spatial scales represented in the GCMs. For example, estimations of temperature at a particular location may be correlated with upper-level pressure patterns and wind fields. The GCM's projections of these pressure and wind patterns would then be used to derive the temperature projections at this location. The mathematical relationships are presumed unchanged when given data from the GCM future climate projections.

Statistical downscaling techniques tie local climate conditions to the large-scale conditions, but provide no feedback from these local conditions to the large-scale conditions. Therefore, these techniques are best applied in regions in which local processes have little influence on the large-scale circulation. A region where climate change is dominated by changes in the frequency and location of large-scale weather systems would be a good candidate for statistical downscaling. A region where feedback between soil moisture and convective rainfall is important may not be a good candidate.

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8. The robustness to changing climate conditions can be compared to a climate change signal to determine regions where lack of robustness may overwhelm the climate change signal.

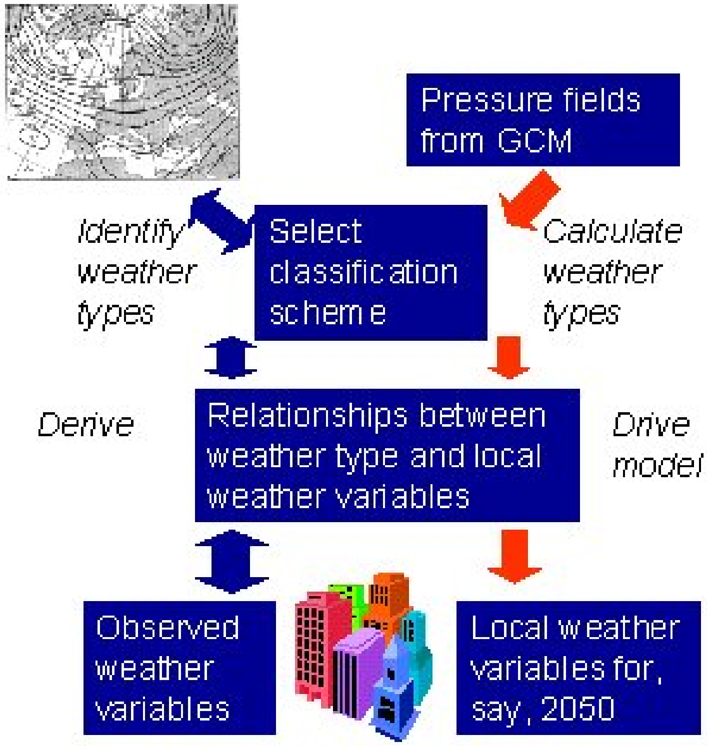

Figure 3.3. Statistical downscaling using classification of weather types based on atmospheric pressure patterns. This figure illustrates some general properties of statistical downscaling such as the derivation of relationships between large-scale and local weather variables in observations, and the use of these relationships in downscaling GCM projections.

Source: Canadian Institute for Climate Studies, 2006.

Three assumptions are implicit in all statistical downscaling techniques.

1. The large-scale climate variables are being modeled realistically by the GCM
2. The empirical mathematical relationships are unchanged when the climate changes
3. The global climate variables are capable of representing the entire climate change signal.

Results show that no single statistical downscaling method is uniformly better than all others in every application. However, it is necessary to be mindful of the limitations of some statistical downscaling techniques. Change factors only change the means and extremes of the GCM output. The range, variability, and spatial pattern generated from change factors remain unchanged, and sequencing of weather events is identical to that of the observations. Regression approaches predict the expected value of the station observations; as a result, they may underpredict the variance. Artificial neural networks are one type of nonlinear regression that consistently performs better in some situations than linear regression methods.

One advantage of statistical downscaling is that it requires much less computer time than dynamical methods and does not typically require GCM output beyond that which is part of the CMIP archives. Therefore statistical downscaling can be applied to a much larger ensemble of GCM output, and can better sample the uncertainty due to differing GCM inputs. Nevertheless, statistical methods need time and effort for preliminary work, such as assembling, reformatting, and quality control of the datasets. Due to the variety of statistical downscaling approaches that could be used, a range of statistical methods should be used, enabling a range of outcomes that reflect uncertainty in the downscaling approach.

Section B.1 in Appendix B contains a brief description of the traditional typology used to describe statistical downscaling techniques. Section B.2 describes three statistical downscaling approaches in use by WUCA members in order to provide examples of the typology categories and the integration of those categories in practice. Appendix C describes characteristics of reliable statistical downscaling practices.

Regional climate models

RCMs use global climate simulations as input to a limited-area model that covers only a portion of the globe (e.g., a continent), but at much higher spatial resolution than a GCM. Like GCMs, RCMs use mechanistic mathematical relationships derived from physical principles, such as conservation of matter and energy. RCMs use periodic updates (usually spaced six hours apart) from GCMs at their boundaries, but simulate the regional climate processes within their limited-area domain.

RCMs are provided large-scale GCM data at periodic time intervals (usually six hours) in relatively small geographic windows (usually 250–750 km) along the border of the RCM domain (Figure 3.4). This means the large-scale conditions in the RCM are incomplete, and there is the potential for either a mismatch of large-scale conditions in the RCM and GCM, or unrealistic feedback of regional processes into the large-scale conditions. RCMs are best applied in regions where regional processes that alter large-scale conditions are well documented in order to evaluate the verisimilitude of observed and simulated regional processes; for example, the feedback between soil moisture and large-scale circulation in the central United States, and the regional pressure response to high-elevation temperature in the Pacific Northwest.

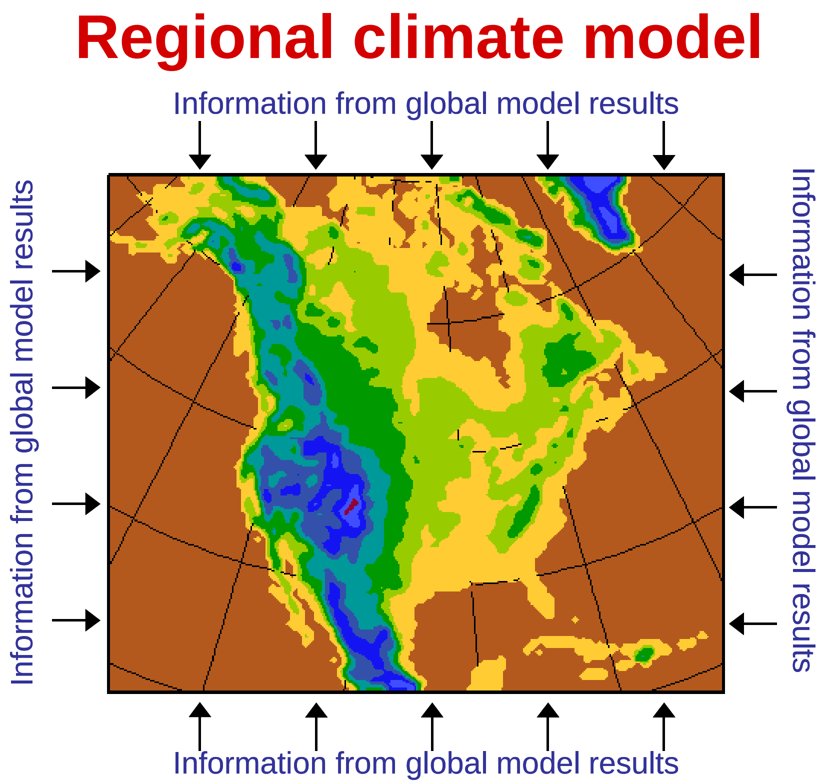

Figure 3.4. A RCM uses information from the GCM at the boundaries of its geographical domain to produce high-resolution detail in the interior. Contours of elevation are shown at the RCM spatial resolution of about 50 km.

Source: Dr. Raymond W. Arritt, Iowa State University, personal communication, May 2, 2008.

Three assumptions are inherent in RCMs:

1. The global climate simulation is skillful at the RCM boundaries.
2. The large-scale conditions can be adequately represented at the RCM boundaries.
3. The RCM parameterizations (described below), are valid under climate conditions different from those in which they were developed. For example, the convective parameterization must correctly respond to different soil moisture conditions expected in the future.

The only conditions that preclude the use of a GCM dataset as input to an RCM are the GCM dataset's accessibility and the existence of software to translate it into the input data format for the RCM. These are not trivial conditions. Data must be input at the RCM boundaries no less than every 12 simulated hours and preferably every six simulated hours. This creates the need for a very large data archive, and it is necessary to have well thought-out methodologies to handle data transfer. This level of coordination between GCM groups and RCM groups is uncommon. As a result, very few global climate simulations are available for RCM simulations. It is this lack of coordination, that generally constrains the choices of which GCM future climate projections are used in producing RCM regional climate projections.

Even with their higher resolution, the spatial extent of some climate processes is too small for explicit simulation by RCMs. These processes are simulated with "parameterizations" in which less complicated mechanistic models are used to represent the impact of missing climate processes on the explicitly simulated processes. Parameterization is described in Section 3.1.1. Processes that are parameterized include radiation (the interaction of solar and infrared with the atmosphere, clouds, aerosols), atmospheric turbulence, surface energy budget and surface runoff, cloud particle processes (droplets, ice crystals, etc., including their formation, growth, freezing, melting, and transformation into rain and snow), and convective storms.

Appendix D describes characteristics of reliable dynamical downscaling practices.

Time-slice general circulation models

Time-slice general circulation models use the atmosphere and land components of a GCM, run at a higher resolution than is possible in the full AOGCM, in order to simulate small-scale detail. The AOGCM is first used to generate long climate simulations with coarse resolution. Upon completion, the atmosphere component model is used again at much higher resolution for shorter sub-periods or "time slices" of the long climate simulation. The ocean and sea ice conditions from the time-slice of the coarse GCM simulation are provided as input to the high-resolution global atmospheric model.

Time-slice global climate simulations lack a fully interactive global climate system. They cannot ensure the large-scale circulation systems, such as monsoon systems, will be consistent with that of the coarser GCM that provides ocean sea surface patterns and sea ice as input. Furthermore, their ability to simulate interannual and decadal variations is entirely dependent on the ability of the coarser GCM to simulate such variations. Time-slice simulations are best used for regions where mid-latitude storm systems and orographic precipitation are important to local climatology.

3.2.7 Have downscaling techniques been evaluated and compared?

The framework for evaluating downscaling errors described in Section 3.2.5 is rarely applied in full. Generally, the evaluations end with documentation of performance of the baseline climate simulation, so that much of the evaluation boils down to a sensitivity analysis of how the results from the baseline climate simulation vary with alternative downscaling design.

One reason for the limited evaluation of downscaling techniques is the project-centric approach to developing these techniques. The lack of coordinated effort means common analytical procedures have not been established; intercomparison of downscaling techniques is rare outside of a particular project; improvements are made to models as they relate to the specific interests of a scientific project, but not necessarily in response to broader user community needs; and common data archive standards are not established. The lack of coordination also has limited the interaction between model developers and potential users of model output, such as water utility planners, creating disconnect between the information provided and the information needed.

The few evaluations of statistical versus dynamical downscaling have found statistical downscaling techniques and RCMs have comparable skill overall (Wood et al., 2004; Schmidli et al., 2006). The choice of downscaling technique usually is dictated more often by the needs of the group using the downscaled climate projections than the results from coordinated, systematic intercomparison. This choice has been based on such factors as the computational limitations available for the study, the regional extent for which the study is concerned, choice of output variables, or the constraints of the system into which the downscaled data are used.

Evaluations of RCMs versus RCMs are often guided by the priorities of a scientific project concerned with a particular mechanistic process – for example, simulating the response of regional hydrological cycle to climate change – rather than the need for water utility planning. The most comprehensive RCM evaluation in the United States will be conducted by the NARCCAP (http://narccap.ucar.edu/). NARCCAP is designed to evaluate multiple-decade RCM simulations using the framework described in Section 3.2.5 without the alternative baseline climate simulations. Results from NARCCAP are just now being reported. More extensive multi-decade RCM intercomparison projects have been supported in Europe (PRUDENCE, http://prudence.dmi.dk/; and ENSEMBLES, http://ensembles-eu.metoffice.com/), and some results from these projects may be applicable to downscaling efforts in the United States.

Experimental procedures for comparison of alternative baseline climate simulations from RCMs has been established by the GEWEX Hydrometeorology Panel Transferability Working Group (http://rcmlab.agron.iastate.edu/twg/) through an Inter-Continental Transferability Study (ICTS; http://icts.gkss.de/index.html). GEWEX is a core project of the World Meteorological Organization World Climate Research Program, and ICTS engages the international community through GEWEX in an experiment that to date includes simulations from six RCMs. The study design consists of seven simulation regions around the globe. Each RCM was best configured for simulation of climate in its native developmental region and then was applied in one of the other six simulation regions without reconfiguration.

Likewise, comparison of statistical downscaling techniques has been pursued more vigorously in Europe than in the United States. Most intercomparisons are performed in support of specific project objections and involve evaluation of a small number of statistical downscaling techniques for a particular region for a couple of variables. By comparison, the Statistical and Regional Dynamical Downscaling of Extremes for European regions (STARDEX) is the most comprehensive intercomparison of statistical downscaling techniques to date and includes over 20 statistical downscaling approaches applied in multiple regions of Europe to a standard set of variables.

The success of statistical and dynamic downscaling intercomparison projects worldwide, even though few in number, has prompted an internationally coordinated intercomparison project under the auspices of a working group within the World Meteorology Organization's World Climate Research Programme. The project, the COoperative REgional Downscaling EXperiment (COREDEX), is comprised of experts in both RCMs and statistical downscaling methods. COREDEX will provide guidance on experimental design considerations, such as domain location and size, grid spacing, and data archive requirements. Although in its early stages, COREDEX has developed target domains focusing primarily on developing countries, though all continents are covered. The simulation period is expected to be 1950–2070 with RCMs no coarser than 0.5° (about 50 km). The relatively coarse minimum RCM resolution is needed to accommodate the technological capacity of developing nations. The experiments expect to make use of at least five CMIP5 global climate simulations as they become available over the next two to four years, and will include RCP 4.5 and 8.5 scenarios. Additionally, a baseline climate simulation will be included that will span 1987–2009.

3.2.8 What results have the climate downscaling evaluation efforts produced?

The key result from evaluations of RCM versus statistical downscaling techniques is that they have comparable skill overall. However, an important idea that has not been evaluated widely is that some of the limitations of statistical and dynamical downscaling techniques may be overcome by using them in tandem. Running dynamical downscaling first and then applying statistical downscaling to the outputs from the mechanistic modeling may allow for simulations of both the station data and feedback of regional processes into the large-scale circulation. Such connections between downscaling methods have not been explored in the United States. However, this is an integral component of the European program ENSEMBLES.[9]

A key result of RCM comparisons is that no single RCM outperforms all others in every aspect. Unless the climate change study has a singular focus, it is recommended that multiple RCMs are used to characterize uncertainty arising from RCM design choices. The RCM evaluation efforts described in Section 3.2.7 have identified a number of design choices that can impact the results of RCM simulations. The choices with the largest impacts are listed below in no particular order.

- *Domain location.* The location of domain boundaries determines whether the data entering the RCM are of high quality. Domain boundaries within regions of complex topography or coastlines are subject to inconsistent results due to mismatch of the surface features in the coarse input data and relatively fine grid of the RCM. In some regions, the location of the domain boundary should be placed far away from regional processes that the RCM is simulating.

- *Domain size.* The size of the RCM's domain determines the control exerted by the GCM data inserted at the boundary on the interior of the domain. A very large domain may permit the RCM to generate a large-scale circulation much different from that of the GCM input data. A very small domain effectively prevents the RCM from generating its own climate information.

- *Interior nudging.* The RCM solution in the domain interior can be combined with large-scale information from the GCM simulation. Called "nudging," this technique is one method to ensure that the large-scale circulation is consistent in the RCM and GCM simulations. However, nudging can prevent the RCM from generating regional information if nudging is too strong.

- *Convective parameterization.* Convective parameterization is the primary source of disparity among RCM simulations of warm-season rainfall. Simulation of precipitation rate and diurnal timing are the primary climate variables affected. Other variables affected may include surface incident shortwave and longwave radiation, surface humidity, and maximum temperature. Additionally, the regional circulation may be affected on a scale as large as the North American monsoon.

- *Cloud microphysics parameterization.* A secondary factor in creating disparity in rainfall and snowfall is the design of parameterizations for cloud particles (droplets, ice crystals, etc.). Different combinations of cloud microphysics and convective parameterizations alter the statistics of high rain rates.

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9. See http://www.ensembles-eu.org/.

- *Surface energy balance, snow pack evolution*. Parameterization of energy transfer across the Earth's surface directly impact maximum and minimum temperatures. Disparity arises in warm-season maximum and minimum temperatures primarily by the amount of energy that is partitioned into evapotranspiration and secondarily by the depiction of cloudiness from the convective and microphysics parameterization. Disparity of cold-season surface weather stems from the snow pack model. Cold-season maximum and minimum temperatures are critical to snowpack evolution and are very sensitive to the snowpack model itself, especially sublimation of snowpack, changes in snowpack albedo (reflectance of radiation), and snow melt by rain falling on snow pack.

- *Grid spacing*. Grid spacing controls the detail of terrain features and the extent to which parameterizations are used. Many RCMs were developed initially by using regional weather forecasting models that themselves were developed with grid spacing of 20–40 km; therefore, they have been most extensively evaluated in this range. Many aspects of regional simulations are better simulated with 20-km rather than 50-km grid spacing. These include, but are not limited to, extreme rainfall and snowfall rates, and seasonal snowmelt. Additional reductions of grid spacing to 4 km has the benefit of removing the need for traditional convective parameterizations, so that disparity in warm-season rainfall results are smaller and result more so from differences in cloud microphysics parameterization.

However, larger errors in the diurnal phase of precipitation have been reported when using 4-km compared to 20-km grid spacing. Thus, simply reducing grid spacing to 4 km is not an easy fix, and it may require additional model development, such as a new convective parameterization. Evaluation of snowfall in mountainous terrain is in a preliminary stage, but shows promising results. RCMs run with grid spacing of 4 km may not show consistent improvements over 20-km grid spacing until new convective parameterization is developed and more extensive cold-season testing is completed.

Evaluation of statistical downscaling techniques has yielded some ideas on which methods tend to perform better for certain variables.

- Bias correction of GCM data prior to application in statistical downscaling techniques can reduce statistical downscaling errors. This is especially true for continuous, normally distributed variables such as monthly temperature and is much less the case for volatile variables such as daily precipitation.

- For long-period average data, such as monthly, seasonal, and annual averages, a single statistical downscaling technique rarely emerges as superior to all others. It is recommended that multiple statistical downscaling techniques should be used to construct many alternative local scenarios.

- Daily temperature and maximum/minimum temperatures have been well simulated in many regions using variations of non-linear regression (such as artificial neural networks), pattern matching/analogues, or combinations of the two.

- Daily precipitation is best simulated with stochastic weather generators, stochastic models (such as Markov models), pattern matching/analogue techniques, or combinations of the above. Furthermore, it is important to include a humidity as one of the predictor variables.

3.3 Key Insights from the Science

This section briefly reviews key insights from the scientific literature that are relevant for understanding the current state of modeling and its ability or inability to provide "actionable" science for use in water resource management. These insights are also important for understanding where investments can be made.

The GCMs evaluated in Solomon et al. (2007) were part of CMIP3. The set of simulations of the 20th-century climate and projections into the 21st century was the result of a coordinated effort involving 22 modeling centers around the globe. These data are very useful for quantifying the uncertainty in our estimates of the global temperature signal.

3.3.1 Insights on global climate modeling

The following insights on global climate modeling are derived from the scientific literature key uncertainties related to water utilities' climate change adaptation efforts:

- The key uncertainty for most applications is in the projected precipitation changes on time scales from annual totals down to occurrence of daily extreme events. This is most likely due to a number of factors.

- Particularly large annual and seasonal precipitation biases exist in historic simulations in most models over the western United States. This may be due to the poor representation of topography and to remote factors, such as the biases in the Tropical Pacific climate.

- Deficiencies in the simulation of warm-season (convective) precipitation exist over much of the United States. Daily precipitation extremes are not captured by GCMs, and the North American monsoon is poorly simulated in most GCMs.

- Though there is general agreement that North America will warm, uncertainty in the magnitude of that warming can also have a significant impact on estimates of future hydrologic changes, because the more temperatures increase, the more the hydrologic cycle speeds up.

- An ensemble of multiple runs of each available model is desirable to separate the time-evolving climate change signal in each model from internal variability. Ensembles are particularly needed for precipitation on regional scales, where so-called “pattern-scaling” techniques may be less reliable than for temperature.

- There is a lack of agreement among models in the way that the Tropical Oceans respond to climate change. Change in Tropical Oceans is a very important factor affecting regional climate patterns. ENSO is a good example, but this extends to decadal and longer trends as well. This lack of agreement among models is one likely source of uncertainty about precipitation changes over the western and central United States (CCSP 3.1, 2008).

- Decadal modes of variability (e.g., PDO, AMO) are poorly simulated in most climate models.

- Though climate variability will continue into the future, there is no consensus on how modes of climate variability (e.g., ENSO, PDO, AMO) will change.

- Uncertainty in climate projections for small regions is not well addressed by GCMs.

The coordinated international modeling effort that will go into CMIP5, and that will be the basis for much of the modeling analysis in AR5, presents the water resources community with a significant opportunity. This effort should be leveraged as much as possible.

3.3.2 Insights on downscaling

The following insights on downscaling are derived from the scientific literature on key uncertainties related to water utilities’ climate change adaptation efforts:

- All downscaling techniques benefit from improvements to GCMs.

- All downscaling techniques benefit from use of bias-correction. Statistical downscaling techniques apply bias correction prior to their use, whereas bias correction can be applied to the output from dynamical downscaling techniques.

- GCM projections are unlikely to produce output at the temporal/spatial scales used in water utility planning tools within the next decade; downscaling will be needed.
- Key uncertainties in RCM simulations of regional climate are:
  - Disparity of warm-season rainfall and rainfall rate due to different convective parameterization schemes
  - Disparity of snow pack evolution due to differences in land surface model (including model for snow pack itself) and microphysics parameterization.
- RCMs with grid spacing of 10–20 km have improved regional simulations in comparison to RCM simulations made with 40–60 km.
- RCMs with grid spacing of 2–10 km have not shown systematic improvements in regional simulations:
  - There is less disparity of warm-season rainfall and rainfall rate due to the absence of convective parameterization; however, substantial error in diurnal timing of rainfall has been documented.
  - Results from cold-season simulations are preliminary but promising.
- Key uncertainties in statistical downscaling are:
  - Sensitivity to stationarity assumptions has only been evaluated for a couple of techniques in recent studies. General claims about the potential error from this assumption need further evaluation.
  - Different techniques produce different, but not necessarily poorer, results. It is strongly recommended that multiple statistical downscaling techniques are used when creating local climate change scenarios.
  - Some statistical downscaling techniques are better suited for daily data. Daily temperature is better simulated by non-linear regression and pattern matching/analogue methods. Daily precipitation is better simulated with stochastic models, weather generators, and pattern matching/analogue techniques.
- Accessibility to climate model data required by models used by water utilities is limited by the number of regional projections available, the number of techniques used, and the types of variables in the archive, such as daily temperature and precipitation.

- Combinations of dynamical and statistical downscaling have not been examined, even though conceptually the strengths of one appear to address the weaknesses of the other.

- Community intercomparison projects and community archives are hallmarks of the downscaling community. They have created mechanisms for careful evaluation of the sources of uncertainty in downscaled climate projections and for engaging decision-makers.

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4. Prospects for Improving the Science

This chapter briefly assesses the general improvements in the science that seem feasible in coming years regarding the four objectives of water utilities. It then presents specific options for improving the science of global climate modeling and downscaling to support the key objectives of water utilities in adapting to climate change.

4.1 Feasible Improvements in the Science for Meeting the Objectives of Water Utilities

In general it is important to note that there does not appear to be a single investment – i.e., the proverbial "magic bullet" – that will make climate change science "actionable" for water utilities (and other potential users of climate model information). Specific science investment options are discussed in the next section. None of these alone will yield an immediate and dramatic improvement in the science. But investing in many or all of them will help improve the science. Even with that, the improvements will be incremental and will take time.

To be sure, over several decades the science of climate change has improved. Ten or more years ago, the common wisdom was that change in regional climates was uncertain. We have long known that increased emissions of GHGs will raise global temperature and sea level. We have also understood the fundamental physical principles that tell us qualitatively where temperatures will rise relatively more and what latitudinal bands will likely see increases or decreases in precipitation. In recent years, improvement in GCMs, inclusion of many GCMs, and development of downscaling techniques have enabled climate scientists to have enough confidence in giving projections of likely and even very likely changes in temperature and precipitation for some sub-continental regions (e.g., Christensen et al., 2007). While such projections are at a scale that is too large for water utilities, they still represent an improvement in the science from previous decades.

It is reasonable to assume that the science will continue to improve. Following are the objectives for improved science desired by water utilities, as stated above, and the improvements in science we think are possible.

4.1.1 Model agreement on change in key parameters

A critical impediment to developing consistent projections of regional climate change is that in many regions GCMs disagree on how key large-scale climate phenomena will change. These phenomena include atmosphere circulation patterns, ENSO and its teleconnections, and storm tracks and precipitation in certain regions. The disagreements also include important smaller-scale processes, such as cloud formation and snow pack development. Understanding and improving the science behind these projections are critical to resolving the differences across the climate models. Several of the options discussed in the next section concern how improvements can be made in simulating a number of these phenomena.

4.1.2 Narrowing the range of model output

Utilities are concerned about the wide range of projections across the numerous emission scenarios and models. This can be the case, even where models agree on the sign of change, such as with temperature. Where the models do not agree on the sign of change it is unclear whether to interpret these results as due to natural variability (thus indicating "probably no change") or due to uncertainty in the climate change signal (thus indicating "probably change, but we don't know which direction"). Identifying the source of the uncertainty in the model changes, and putting these in the context of all sources of uncertainty in climate projections is needed.

Fundamentally, it seems that little progress can be made in narrowing the range solely through model improvements. One reason is that GHG emission scenarios differ widely. By late in the 21st century, Houghton et al., 2001 (the IPCC's Third Assessment Report), Fourth Assessment Report (Solomon et al., 2007), and *Special Report on Emissions Scenarios* (Nakićenovic et al., 2000) scenarios have a more than a four-fold difference in carbon emissions (Nakićenovic et al., 2000). As noted above, the newer emissions scenarios being developed for IPCC's AR5 are if anything widening this range. So there seems to be little prospect for reducing the range of uncertainty about emissions scenarios in the next few years.[1] Note, however, that the new scenarios explicitly include assumptions about mitigation policy (reduction of GHG emissions). The effectiveness of these policies in the long run, however, will remain a source of uncertainty.

A second reason for little progress is climate sensitivity – how much global mean temperatures increase with CO_2 doubling when the models are run to equilibrium. The IPCC concluded that the there is at least a two-thirds probability that the range will fall between 2 and 4.5°C. Roe and Baker (2007), among others, see little hope for substantially reducing this range through model improvement within several decades. Because individual GCMs have different climate sensitivities, they produce different magnitudes of climate change. The temperature change over the next century, however, is better constrained than the long-term equilibrium climate sensitivity.

1. Note that the effect of different emissions scenarios on global temperatures is not distinguishable until about the middle of the 21st century. This means that for the next few decades, the difference in emissions scenarios is not important for projections of regional climate change.

The final reason is that individual models project different patterns of regional climate change (as discussed above). There is, perhaps, some hope that this source of uncertainty could be narrowed through a convergence of GCM simulations of the Tropics. Given this situation, the best that might be accomplished is to better understand the distribution of projections and enable scientists to communicate more effectively their confidence in certain processes of change. As discussed below, development of common datasets in data archives that contain outputs from many models will enable the user community to assess differences and distributions across emission scenarios and models.

4.1.3 Model resolution at spatial and temporal scales that match water utilities' current system models

Water utilities use system models (e.g., supply, demand, operations) to guide their planning, and these models often require input at spatial and temporal scales finer than that provided by climate models. The requirements of some of these models for the WUCA member utilities are discussed in Chapter 2 and in Appendix A. What would be ideal is if the resolution of the global models could be at a scale useful for utilities. As discussed in Chapter 3 and below, climate model resolution is improving, and eventually this disparity in scales is likely to be eliminated. But these gains take many years to be realized. Even as these improvements in resolution are made, they do not necessarily guarantee substantially improved accuracy. So, in the meantime, downscaling remains the best option to produce higher-resolution projections. As noted above, downscaling by itself does not necessarily correct for large-scale errors in the GCMs.

4.1.4 Improved projections within water utility planning horizons

Planning horizons for water utilities often extend out only a few decades, although capital projects are projected to last for many decades, and some utilities plan for up to century time scales. The difference in planning horizons is important for the reliability of climate change projections. Climate variability, particularly for precipitation in many areas of the United States, is likely to dominate the climate change signal out to about three decades. This means that within that timeframe, the observed climate change with respect to a historical reference period will be influenced as much by variability as by increased GHG concentrations, and planning methods will need to take both these factors into account. To develop reliable projections for the next three decades, we will need to be able to better predict climate variability. Predicting such phenomena as ENSO, the PDO, and the AMO will be necessary to develop more reliable projections within such a time period. Beyond about three decades, the climate change signal is expected to become stronger than climate variability. For planning horizons out that far into the future, the improvements under the three topics discussed above are necessary to yield more reliable projections.

4.2 Options for Improving Climate Models

This section presents options for improving climate projections to help make the science more "actionable" for water utilities. Options for improving global projections are presented first, followed by options for improving downscaling and a table that summarizes the investment options.

The options attempt to address the four key improvements stated in Section 4.1. The various components that need to be in place to address these improvements are stated in the individual recommendations. They describe a vision of what is needed to create "actionable science" for water utilities in the next decade. This vision encompasses a coordinated ensemble of global and regional climate projections at the spatial and temporal scales needed for water utility applications, improved use of climatic observations to constrain the models and methods, and greater accessibility of the downscaled data to the water resources community. We approach the topic broadly to consider development, improvement, and evaluation of GCMs, RCMs, and statistical downscaling techniques; the implementation of coordinated sets of model runs to address climate change uncertainties; and the archiving and dissemination of downscaled climate projections.

There are basically two types of options. One involves improving the understanding of how the climate system works and how it is represented in models. We are extremely confident that these improvements will happen, but improvements do not happen overnight and indeed they can take a decade or more to be realized. The other set of options involves doing more with the data from climate models that are already available. This involves improving the archiving and targeted analysis of model output. This work can begin immediately and could produce results within a few years. Analyzing results from many models can give insight into better understanding and communication of regional changes in climate.

The estimates of costs should be considered as preliminary. They are meant to be approximate so readers can get a sense of the order of magnitude of costs that may be involved in these efforts, i.e., are these needs in the hundreds of thousands, millions, or tens of millions of dollars? These very rough estimates are based on what the authors believe would be needed in addition to existing efforts, and assumes that the existing efforts continue to be funded. These estimates are for U.S. efforts, though international collaboration would be beneficial in achieving many of the stated goals. While developed with the WUCA members' needs in the forefront, these objectives would also benefit a much broader spectrum of water resources applications, and indeed applications in other sectors as well. In identifying the resources needed, we focused on the ones that we felt would drive the overall cost, and doubtless omitted many details. We based the estimates on a brief examination of what comparable resources have cost in the recent past, e.g., the costs of supercomputers and smaller-scale computational clusters, data storage, and research grant programs. Development of programs to implement these options would require a separate, detailed planning and coordination effort.

4.2.1 Options for improving GCMs

To produce "actionable science" and address the above needs, we see the following specific goals for improving global climate modeling:

1. Improve the confidence in the range of GCM climate projections through better understanding of the sources of uncertainty in the climate models on global and sub-continental scales.

2. Improve the accessibility of GCM projection data to statistical and dynamical downscaling groups.

3. Improve the ability to assign credible probabilities to GCM model scenarios based on advanced comparison of the models to observations.

4. Develop the ability to integrate projections of climate variability, particularly decadal variability, with projections of climate change. This is particularly important for projections of three decades or less.

5. Improve GCM model simulations to increase accuracy at the scale of the GCM and therefore provide better input to downscaling methods.

6. Improve agreement on the sign of change (for variables where there is currently disagreement), rate of change, and reduce the range among GCM projections in key parameters of the *global and regional* climate on the timeframes of interest to water managers.

We believe that the following options will result in improved science or understanding of the science to help the water resources community adapt to climate change.

GCM-1. Develop and enhance GCM ensembles

This effort will result in the creation of ensembles of GCM projections of at least the next 50 years. It will lead to increased confidence in the ranges of GCM projections through better understanding of sources of uncertainty. It will also form the basis for the development of regional climate change ensembles discussed in downscaling option DS-1. The existing plans of the many modeling centers around the globe to contribute to CMIP5 will address some of the goals noted above. In addition, we propose to leverage the CMIP5 modeling effort through enhanced data distribution, modeling, and analysis to better address the regional climate change problem on the time horizons of many water utilities' planning needs. We propose the following enhancements:

- Perform large (10–30 member) ensembles of projections for each GCM out to at least the year 2060 at multiple modeling centers at a resolution of 50–100 km in the atmosphere component, and with high resolution in the tropical oceans. This ensemble should probably be performed with traditional AOGCMs, rather than with ESMs (with an interactive carbon cycle component), because AOGCMs can be run at higher resolution and they are a "known quantity" compared to ESMs.

- Archive sufficient GCM output data over the North American domain for use as input to dynamically downscaled runs of continental, regional, and local areas, for the entire time history.

- Archive and disseminate a subset of GCM output variables over the North American domain at appropriate spatial and temporal scales. These data would be used for the detailed evaluation of model performance, statistical downscaling, and development of probabilistic estimates of regional climate change for water resources and other applications.

- Coordinate with modeling centers worldwide to meet the above goals for as many models as possible in the CMIP5 archive.

Due to limitations on computer resources, there is a tradeoff between running a model with increased resolution and creating larger ensembles at lower resolution. At present we side with larger ensembles over higher resolution. To create these ensembles we recommend model resolutions of ~100 km as an appropriate tradeoff between these two factors at the present time. We recommend going to higher resolution only if greatly improved accuracy in simulating the *global* climate and in reducing the main GCM biases over North America can be convincingly demonstrated. The models could then provide more credible input for dynamical and statistical downscaling. The precipitation bias over the western United States (where large errors exist in most current models) is particularly important in this regard. For example, if a GCM greatly reduces its climate biases globally and over North America when run with a 50-km atmosphere (or a high resolution ocean, for that matter), then we would recommend that resources be made available to perform a smaller ensemble of simulation at the higher resolution.

Pros

- Larger ensembles will allow clearer discrimination between the regional climate change signal of a model and the model's internal variability. This will improve the level of scientific understanding of two dominant sources of uncertainty in regional climate projections.

- Larger ensembles will provide a richer set of model scenarios for use in time-dependent adaptation studies, as well as traditional time-slice studies.

- Larger ensembles build on the strength of the existing CMIP program, and can be accomplished quickly if adequate resources are made available.

- Larger ensembles build on the experience of the European Union ENSEMBLES and PRUDENCE programs. Coordination between GCM modeling and regional downscaling, with the involvement of stakeholders, leads to a better scientific understanding and more actionable science (Hewitt and Griggs, 2004).

- Benefits will extend far beyond water resource applications to a better understanding of global and regional climate uncertainty.

- Traditional climate projection methodology with AOGCMs is well established, compared to ESM projections and decadal climate prediction. For example, decadal prediction models may suffer from systematic "drift" in climate as the models adjust from the observed initial conditions to the model's preferred climate.

- GCMs at 50–100 km resolution have been developed and tested at several modeling centers (e.g., NCAR, GFDL, Hadley Centre), so implementation is expected to be straightforward.

- Larger ensembles will facilitate a coordinated effort to produce ensembles of regional climate change projections (see Downscaling 1) through statistical and dynamical downscaling.

- While decadal predictions are planned (see recommendation GCM-4) out to 2035, water utilities need information on longer time horizons

Cons

- Running large ensembles will limit running models at higher resolution. Until there is clear evidence that higher resolution leads to a convergence among different models, we recommend a better sampling of the range of uncertainty through running ensembles.

- It may be feasible to dynamically downscale only a small subset of ensemble members for each GCM.

- Data storage and dissemination requirements may be a limiting factor if higher-resolution GCMs are used.

- Larger ensembles require international cooperation/funding to obtain participation by a large sample of modeling centers.

- Many modeling centers have already decided on computer allocations for their initial CMIP5 runs, which may cause delay for the enhanced ensembles until after these runs are completed in 2011.

- As in CMIP3, plans for CMIP5 may have to be scaled back at some modeling centers due to unanticipated difficulties or limitations on computational resources.

Availability

Coordination with U.S. climate modeling centers, the IPCC Working Group on Coupled Models, and coordinators of CMIP5 should begin as soon as possible. Even then, it should be recognized that many modeling centers have well-developed plans and computer allocations.

The plans for CMIP5 include a “Core” set of runs, as well as optional “Tier 1” and “Tier 2” runs (Taylor et al., 2009). While the Core runs will include only small ensembles, there is the option under Tier 1 of producing larger ensembles. However CMIP5 is only a coordinating framework; the choice of which runs are performed is made by the individual modeling centers. The greatest chance for water utilities to influence the choice of model runs lies in the period immediately after AR5 runs are complete.

Therefore, only a subset of these runs may be feasible by 2011 as part of existing CMIP5 plans, with full completion after that date. Timeframe: 2–7 years.

Estimate of costs

Enhanced data archiving and dissemination of the large amount of climate model output would be needed. CMIP5 is planning a distributed archive accessible through the Earth System Grid. The Program for Climate Model Diagnosis and Intercomparison was the main archive for CMIP3, will play a major role in serving CMIP5 data, and provides an example of the scale of the organization needed to serve this purpose. The capabilities of the distributed data archives would need to be augmented by several hundred terabytes to archive the global model output from these runs.

Archiving the specific GCM output needed as input to downscaling methods should be done as part of the regional climate projections data center proposed in option Downscaling 1, where its costs are estimated.

Additional computing resources would also be needed. This project does not require the development or deployment of new computer architectures, merely more computer time on the existing or newly procured supercomputers to be devoted to this project. At 100-km resolution, estimated resources would be in the range of \$3–5 million dollars for U.S. modeling centers over five years (i.e., the cost of a small supercomputer). At 50 km, but with fewer ensemble members, estimated resources would be closer to \$10–\$30 million over five years (i.e., the cost of a medium-sized supercomputer). The cost could be greatly reduced if computer time on existing machines is allocated for this project. Additional data archiving and access services could cost as much as \$1 million/year, based on market rates for online storage.

GCM-2. Improve use of observations to constrain climate models' projections

One of the fundamental reasons there is a wide range of projections of regional climate change is the uncertainty about climate sensitivity: how much global average temperature will increase with doubling of CO_2 concentrations in the atmosphere. This effort will develop and apply new methods to use observations of the past climate and the emerging climate change signal to narrow the range of climate model projections where possible. These techniques will enable better estimation of the likely range of global temperature change, and of regional patterns of climate change for temperature and precipitation. These techniques can also aid in the choice of GCM parameters to produce more accurate simulations of the climate. Finally, improved methods for assigning credible probabilities to different magnitudes of climate change should be developed.

"Detection and attribution" studies use a combination of models and observations to answer the questions, "Is there a trend in the observed data, and how likely is it to be anthropogenic?" While many climate trends have been detected on local and regional scales, attribution of these trends to human causes can be problematic due to the large climate variability on these scales. These difficulties are particularly pronounced for precipitation due to its large variability. At present, the performance of a model in simulating the observed climate provides little guidance regarding which models to use in a climate change assessment, and little help in narrowing the range of projections. One recent study postulated that improving GCMs may not ultimately reduce the uncertainty in projections of global averaged temperature due to the number and complexity of interacting processes (Roe and Baker, 2007). However, a more sophisticated use of observational data, along with the emerging climate change signal over the next two decades, may have a good chance at breaking this deadlock.

This effort would include funding of research that includes:

- Improving the evaluation of GCMs through development of metrics that are better indicators of regional climate change, and in particular regional hydrologic change.
- Extending statistical detection and attribution studies that combine observed data and climate model output to improve probabilistic estimates of the magnitude of the observed anthropogenic climate change signal on both global and regional scales.
- Developing advanced statistical methods to combine observations, GCMs, and RCMs to improve probabilistic projections of regional climate change out to the mid-21st century.
- Applying advanced data assimilation techniques to climate and Earth system models in order to (1) better estimate the global and regional trends in all aspects of the climate system, with a particular emphasis on better constraining the hydrologic cycle, and (2) improve climate models by better constraining the values of parameters in the models.

Pros

- This effort builds on work on Bayesian methods (Tebaldi and Lobell, 2008), fingerprinting, and numerous other attribution and signal estimation studies.
- Time is on our side. As the climate continues to warm, there will be better observations of how global and regional climates are changing.
- Despite all our efforts at improving climate models, careful measurement of the emerging climate signal may be our best hope for reducing uncertainties.

Cons

- Data assimilation is technologically complex and computationally intensive.

- Data assimilation for climate models requires better models and better observations, particularly of the oceans. Waiting for improvements in these areas may delay results. Estimation of ocean heat uptake is critical.

- Time is also our enemy. These methods may not significantly narrow the range of projections by the time a decision needs to be made. Even with investment in this area, policymakers may still have to live with a large range of uncertainty in climate projections.

Availability

The first results could come in as little as two years for the application of improved statistical methods to the CMIP5 model runs. Development of data assimilation for ocean models is an ongoing effort. Extending this to the coupled atmosphere-ocean-land system would take at least 5−10 years, while developing a full Earth system model data assimilation system might take a decade or more. Also, it may take a decade or two for the observed climate change trends to become large enough to narrow the range of projections.

Estimate of costs

- Funding additional research in statistical methods of enhanced detection and attribution: $2–$5 million per year.

- Development of a single GCM climate data assimilation system: millions of dollars per year, though this could be lower depending on existing programs.

- Integration of data assimilation techniques into model development: several million dollars per year, including computer time needed. As above this could be lower, depending on leveraging existing programs.

GCM-3. Improve modeling of the tropical Pacific

The climate of the Tropics, and of the tropical Pacific in particular, exerts an important influence on the climate of North America. (As noted above, this is quite evident in ENSO cycles, but it is also true for the average climate and for decadal variations as well.) The current generation of climate models (AOGCMs) do not agree in their historic simulations or projections for the tropical Pacific. Thus, they are a source of uncertainty in the precipitation projections around the globe, particularly in the western and central United States. It is encouraging that atmosphere-only GCMs show good agreement in their simulation of North American precipitation when presented with the historical record of tropical ocean temperatures. Therefore, the target of this project would be to improve the simulation of tropical Pacific Ocean temperatures in AOGCMs.

This effort would fund a focused research program combining modeling, observations, and theory with the goal of reducing climate model bias in the tropical Pacific, and seeking convergence among the models in projections for this region on all time scales, but with an emphasis on the climate change signal. A particular focus of this research should be in using the observed data to constrain the ocean and atmosphere models. An innovative method would be to integrate ocean data assimilation into the model development cycle.

So far, there has been no systematic approach to improving the tropical simulations. Because phenomena such as the seasonal cycle and ENSO are the result of the interaction of many processes in both the atmosphere and the ocean, improvements in one area of the climate model may actually lead to a poorer performance in simulating another. For example, the Hadley Centre model HadCM3 had one of the best ENSO simulations of the CMIP3 models. The next generation of the Hadley Centre model – HadGEM1 – had a much poorer simulation of ENSO. In another example, the NCAR CCSM3 model had an unphysical El Niño with a strong two-year cycle (Deser et al., 2006). Neale et al., 2008 report great improvements in a later version of that model, though at this writing we do not know whether these improvements will be seen in the version that NCAR will use for the next CMIP5 projections. Yet we are still in a situation where most climate models are not able to reproduce El Niño amplitude and recurrence within observational error bounds. We discuss ENSO here only as emblematic of the inherent difficulty in obtaining and maintaining improvement in Tropical climate simulations. In sum, the reasons for improvement or degradation of the model simulation are often poorly understood. Therefore, new methods need to be brought to bear on this problem.

The increasing availability of ocean observations has been accompanied by the development of more sophisticated “data assimilation” techniques. These techniques blend model and observation to estimate the evolving state of the ocean in the past and to provide initial conditions for seasonal and decadal predictions. We feel that it is in these techniques that there is the best hope for systematically improving the simulation of the Tropical Pacific.

Pros

- This is one of the few options that might narrow the range of precipitation projections over North America, as it addresses the source of some of these discrepancies in teleconnections from the Tropics.
- Convergence of models here would have payoffs for prediction on multiple time scales.

- This option can build on work with coupled models and data assimilation used for seasonal (ENSO) and decadal prediction.
- The tropical Pacific Ocean is comparatively well observed: the Tropical Ocean and Global Atmosphere/Tropical Atmosphere-Ocean Array has been collecting sub-surface ocean data for almost 25 years.
- Starting around 2000, ARGO floats (http://www.argo.ucsd.edu/) have provided unprecedented spatial and temporal observations of the upper 2,000 meters of ocean with nearly global coverage, including the Tropical Pacific.

Cons

- This option has a low certainty of success. This is a difficult problem given that progress on this has been slow and not systematic across models in the last decade, and it requires innovative ideas.
- Natural multi-decadal variations in ENSO amplitude may prove too large for useful predictions of change in ENSO characteristics to be reliable.
- This option requires collaboration across disciplines, which may take time to develop.
- This option requires cross-modeling center coordination, which may prove technically and organizationally difficult.

Availability

Some progress could be made in 2–5 years through analysis of existing data to better evaluate climate model performance in the Tropical Pacific. Additional progress could be made by intensively analyzing the Tropical Pacific in coordination with the decadal prediction component of CMIP5 which will start their coupled models using simplified ocean data assimilation methods. However, the larger project of using data assimilation methods to directly improve climate models, and transferring knowledge and techniques from the seasonal prediction models to climate models is much more complex and will likely take longer.

Estimate of costs

- Intensive analysis of climate model performance in the Tropics, including decadal predictions models, could be supported by a research program on the order of $1–3 million per year.

- The larger program of coordinated model evaluation and improvement in the Tropical Pacific would likely require a multi-million dollar research program, possibly up to $10 million per year. The main needs are the support of research teams to develop and apply advanced data assimilation techniques to climate models, along with the large computing resources that this would require.

GCM-4. Evaluate decadal prediction efforts for water utilities' planning

Prediction of the future climate that takes into account both the climate change signal and the phase of natural climate variability is referred to as "decadal climate prediction" (see Section 3.1.2). Decadal climate prediction is a new methodology with great uncertainties, but also has the potential for great benefit to water utilities. CMIP5 will include the first intercomparison of decadal predictions. Decadal prediction runs are planned to extend to 2035 using GCMs with 50–100 km resolution in the atmosphere.

This effort would fund:

- A climate change specialist to track the progress of decadal prediction efforts worldwide and evaluate the potential for using decadal predictions in water utility planning.
- Research to integrate predictions of climate variability on annual-to-decadal scales with projections of climate change, thus providing climate change information to address a range of planning horizons.
- Downscaling efforts only if the potential skill of these prediction can be demonstrated through "hindcast" experiments.

Pros

- Some water utilities have expressed a desire for predictions on a 2–10-year scale.
- This option may provide improved regional projections because oceans start closer to observed conditions than in free-running GCMs.
- This option has the potential for skill in predicting Atlantic and Pacific decadal oscillations, potentially improving predictions over most of North America.
- This will be a large, international effort that is worth following.
- This option will enhance the understanding of decadal variability and the ability to integrate decadal variability with climate change.

Cons

- Predictive skill may be too low to be useful. It is unclear how much predictive skill there is in addition to what we already know: ENSO (6–12 month lead time) and the anthropogenic trend (decades).
- Many methodological issues need to be worked out regarding how to initialize the models to the observed ocean conditions.
- Hence, the benefits of these predictions to water utilities are not clear.
- This option has a low probability of success (but high potential reward).

Availability

Ensembles of decadal prediction runs are being performed as part of CMIP5 and should be delivered to the archive by 2011.

Estimate of costs

A relatively small commitment of resources would be needed to track and evaluate the usefulness of this new science for water resources planning. A research granting program to evaluate the results for water resources would require funding on the order of less than $1 million per year. Greater involvement could follow if the science of decadal prediction demonstrates its full potential.

4.2.2 Options for improving downscaling

The potential investments in downscaling techniques described below reflect the following priorities.

1. Improve the ability of scientists to express their level of confidence in regional climate projections.
2. Improve the accessibility of local projections.
3. Improve the capacity for water utilities to select scenarios based upon water utilities' management techniques, rather than the ad hoc approaches now employed that are limited to the choice of variables saved for the CMIP3 archive (determined without consultation with water utilities) and the good graces of the few GCM centers that have

created additional CMIP3 archives, containing data suitable for RCMs and statistical downscaling.

4. Reduce the range of climate projections where possible.

5. Address the climate information needed for water utilities planning; however, DS-1 may have a much wider impact so long as decision-makers and experts from other fields were involved early in its implementation.

Following are three standalone investment options for improving the actionability of downscaled climate change projections. Although the expected benefits of investment in each option are not dependent on investment in other options, synergistic benefits may be incurred if more than one investment option is pursued. It should also be recognized that some of the activities described in the investment options are ongoing, and that additional investments primarily affect the scale of the effort, which should accelerate the ongoing work.

DS-1. Develop regional and local climate change ensembles

This option will produce large ensembles of local projections by combining the strengths of statistical and dynamical downscaling, using RCMs at a resolution that is both scientifically justifiable and relevant to water utility planning and statistical downscaling techniques for relevant variables. Although some improvement in representing regional climate processes is expected by reducing RCM resolution, this investment option addresses primarily the lack of infrastructure to perform the simulations, coordinate the work, and distribute the results. The main benefit will be a vast improvement in understanding how uncertainty arises in local projections, what confidence can be placed in them, and how uncertainty and confidence can be effectively articulated to water utilities. All of the components needed to produce this dataset are in existence.

It should also be noted that the cost of this option can be trimmed considerably, particularly in the costs for computing facilities and external grant programs, by focusing only on the statistical downscaling portion.

- Perform RCM simulations that conform to the evaluation strategy in Section 3.2.5 (baseline climate simulation, alternative baseline climate simulation, historic simulation, future projection) using multiple RCMs with grid spacing in the range of 10–20 km. Ideally, this would be coupled with investment option GCM-1, and the framework of COREDEX would be used as guidance. An alternative approach is to build on existing programs through an expansion of the NARCCAP.

- Develop statistical downscaling tools that can be applied to RCM output. Ideally, a wide variety of statistical downscaling techniques would be applied, and the locations and variables for which they are developed would prioritize the requirements for water utilities' decision aids.

- Adapt approaches for quantifying uncertainty and scientists' confidence in the robustness of regional climate changes.

- Archive the datasets generated above in a manner that encourages access. Local projections would require an archive that is web-accessible, has large bandwidth, and permits extraction of probabilistic data as well as data from individual projections for single or multiple points [aspects of this type of access have been nicely prototyped by the LLNL-Reclamation-SCU downscaled climate projections derived from the WCRP's CMIP3 multimodel dataset, stored and served at the Lawrence Livermore National Laboratory (LLNL) Green Data Oasis]. Full output from RCMs simulations should be stored but not necessarily accessible in the way envisioned for local projections in order to control bandwidth.

Pros

- Scientists will be able to communicate more effectively their confidence in local projections. The ensemble of regional simulations will allow them to understand what aspects of regional climate change are insensitive to model design, emissions scenario, and climate variability and to examine climate change in the context of variables not yet analyzed.

- Water utility planners (and the general public) will have an archive of local projections that will allow them to select climate change scenarios based upon their management strategies, including novel approaches that may not yet be used widely in practice.

- Water utility planners will have a voice in the design of regional climate change scenarios and the data archive, including such elements as land-use scenarios for regional simulations.

- Water utilities will have an ongoing dialogue with climate change scientists and statisticians that will enable a more thorough understanding of how climate change datasets are created, how they may be used, and how to access them.

- This effort will establish the infrastructure needed to update climate projections as climate modeling continues to become refined. If organized quickly, it could center on the CMIP5 data release that is tentatively planned for 2011.

- Models of how to organize these efforts and establish a community archive are in place. Santa Clara University and the U.S. Department of the Interior's Bureau of Reclamation have created arguably the most comprehensive archive of statistically downscaled climate projections for the United States. The NARCCAP has established a community of RCM groups, an archive strategy, and methods for evaluating a common domain.
- Other sectors may benefit from this dataset.
- This option may be scaled down to include only the statistical downscaling component, which would be best applied if investment option GCM-1 were pursued rather than to existing datasets.

Cons

- This is the most expensive option for investment in downscaling techniques.
- It requires a high level of effort and coordination among a diverse group of scientists, statisticians, and water managers and will involve a number of federal, academic, and private institutions and agencies.
- It requires new climate services infrastructure and capacity for data storage and access within the federal system (potentially time-consuming activities) to support and coordinate the activities.
- The connections to GCM groups that are needed for RCM simulations are tenuous at this time.
- Focused effort on ensemble techniques may take away time from efforts to improve RCM model components, such as convective and snow pack parameterization.

Availability

- If action is taken within a calendar year of this report, the new datasets would become available in 2–5 years.

Estimate of costs

- New climate services infrastructure is needed to support the collection, archive, and dissemination of local projections and regional simulations. This includes investments in human capital, data archival resources, and maintenance that may be similar in size to NOAA's Climate Data and Information Program under the climate research subactivity, requiring $5–$10 million annually by the climate services organization.

- Computing resources will be critical to completion of RCM simulations in a timely manner. One approach is to provide centralized computing services to all RCM participants. This may be accomplished by dedicating existing computing resources at a large computing facility, expanding the computing resources at a large computing facility at a one-time cost of $10–$15 million (based upon recently purchased very large Linux Clusters – petascale computing not needed), or leveraging on the existing computing facilities of the RCM groups.

- Scientists and statisticians will need funding to complete and analyze the RCM simulations, to develop and apply statistical downscaling tools applied to RCM output, and to adapt approaches for communicating uncertainty and confidence in local projections. The level of effort needed will be similar to funding for an external grants program of about $10 million annually for five to ten years (five-year total investment of $50 million; 10 year total investment of $100 million).

DS-2. Develop RCM model components

Improve variables such as daily precipitation and maximum and minimum temperatures. The end result of this effort will be improved output of RCMs and documentation of their performance relative to the information needed for water utility planning. RCM evaluation must follow the evaluation framework of Section 3.2.5 in order to strictly quantify improvements in performance of variables relevant to water utilities. The relevant variables targeted by RCM improvements below are seasonal, monthly, daily rainfall/snowfall, maximum storm rainfall, storm total rainfall, and daily maximum/minimum temperatures. Two other variables are considered – runoff (snowpack melt) and urban land use – that would represent experimental uses that tie RCMs more closely to water decision aids for runoff and demand estimation.

The main benefit will be improved realism of process simulations by RCMs that are relevant to variables of interest to water utilities. The improved realism may result in improved reliability that may be described in qualitative terms, as in a scientist expressing greater confidence in the RCM simulation, or in quantitative terms in the sense of better accuracy of baseline climate simulations or less degradation in alternative baseline climate simulations, though such quantitative improvements cannot be guaranteed.

The RCM design considerations that should be prioritized follow (note that they are not listed in order of importance):

- Improve seasonal, monthly, and daily amounts in rainfall/snowfall and daily maximum/minimum temperatures at the scale of station measurements when using grid spacing in the range of 2–10 km.

- Estimate maximum storm rainfall and storm total rainfall from current generation of convective parameterization (or lack thereof) and microphysics parameterization are realistic when applied at 2–10 km grid spacing.

- Improve rainfall/snowfall statistics (seasonal, monthly, daily, storm maximum, storm total) by using microphysical parameterizations that use either multi-moment or binned approaches.

- Improve rainfall/snowfall statistics by new convective parameterization developed for 2−12 km grid spacing range.

- Improve runoff estimates by improving land surface representation of river routing and water management infrastructure, such as reservoirs, in conjunction with using RCM grid spacing of less than 5 km. (Experimental work, not necessarily related to approaches for estimating runoff already in place.)

- Improve timing and amount of snowpack melt by adding snowpack components to land surface models. (Experimental work on runoff modeling, not necessarily related to approaches for estimating runoff already in place.)

- Improve minimum/maximum temperature at the scale of station measurements by more detailed representation of urban areas (perhaps useful for demand estimates). (Experimental work, not necessarily related to approaches for estimating demand already in place.)

New observational datasets may be needed to evaluate RCM modifications, and their cost is difficult to estimate. For example, evaluations of microphysics and convective parameterizations may be improved by an enhanced capacity for remotely sensed data of cloud properties, such as a national network of dual-polarization Doppler radar and satellites with lidar (e.g., CloudSat). Observational datasets could also be enhanced with a long-time horizon research facility focused on water measurements within a particular region, similar to the DOE Atmospheric Radiation Measurement Southern Great Plains site.

Pros

- RCM development will target model components (spatial resolution, microphysics parameterization, convective parameterization) and evaluate variables (seasonal, monthly, daily, storm total, storm maximum rainfall/snowfall, maximum/minimum daily temperature) most relevant to water utility planning.

- Scientists will be able to better communicate to water utility planners their confidence in simulations of regional climate dynamics and the implications for climate projections.

- There is the potential for partnering between individual RCM development groups and water utility planners.

- Improvements to RCMs are often transferable to GCMs, as spatial resolution in GCMs increase allowing them to simulate more regional details.

- Evaluation of RCMs with 10–20-km grid spacing is expected to show improvements to storm-total snowfall, timing of seasonal snowmelt, and high-rate rainfall. Additional investment in microphysics and snow pack parameterizations may improve storm-total snowfall and episodic and seasonal snowmelt. Additional investment in 2–10 km grid spacing may show improvement in high-rate rainfall.

Cons

- Investments solely in RCM design may redirect efforts away from ensemble approaches or statistical downscaling, so that while RCM simulation of variables critical to water utility planning may improve, the development of ensembles of local projections is not ensured.

- Current observational systems may be inadequate for detailed evaluation of new model components.

- RCM output will likely still not mimic actual station measurements and still will likely require statistical processing, such as bias correction, in order to use it as input to hydrological and decision system models.

Availability

Evaluations of some RCM component tests could begin within the year, with experiments continuing for the next 10 years. Evaluations of some components, such as choice of grid spacing and utility of multi-moment or binned microphysics parameterization, may be completed by the next round of CMIP, which is scheduled for 2011.

Estimate of costs

- An investment in research staff will be needed, similar to the level of funding from an external grants program, such as the recent DOE Request for Proposal (RFP) for high-risk, high-reward regional modeling that contained about $2 million per year: $5 million/year for 5–10 years (five-year total of $25 million; 10-year total of $50 million).

- This option will require support for general investments in computing resources available to the research community. It may be necessary to invest in computing resources for a particular institution: $1–$5 million one-time investment.

- Observational platforms may need improvement, but it is difficult to estimate the cost of doing so. The President's fiscal year 2010 budget contains an additional $1 million for phased-array Doppler radar, increasing the program funding from $3 million to $4 million. The total cost of the CloudSat program is reported to be $100–$150 million.

DS-3. Develop statistical downscaling techniques for probabilistic downscaling, extremes, and daily data

This option would improve statistical models by investing in simulation of daily data, extremes, and enabling application of probabilistic techniques. The end result of this effort will be wider evaluation of statistical downscaling techniques for variables of interest to water utility planning, focusing on seasonal, monthly, daily, storm total, storm maximum rainfall/snowfall and maximum/minimum temperature. Evaluations of statistical downscaling techniques would follow the framework in Section 3.2.5, so that errors due to stationarity assumptions and GCM errors are clearly documented and their magnitudes can be compared to the magnitude of climate change. New techniques would be encouraged that can emulate regional responses that otherwise would require RCMs to simulate. While this option aims to advance the field of statistical downscaling, it does not ensure that new local projections are generated or archived in an accessible manner.

- Quantify the error range of statistical downscale output due to assumption of stationarity and imperfect GCMs by systematic intercomparison, following the framework of Section 3.2.5, of established methods for statistical downscaling of monthly temperature and precipitation, given identical downscaling periods and input datasets.

- Develop new techniques that produce daily time series of rainfall/snowfall and maximum/minimum temperature, and storm total rainfall/snowfall and storm maximum rainfall/snowfall.

- Conduct systematic evaluation of the relative value of downscaling weather variables for input to hydrology models, compared to using statistical/stochastic models to generate stream flow time series.

- Develop new techniques that produce probabilistic values, including ensemble methodologies that are comprised of combining output from multiple statistical downscaling techniques, including novel ones developed for daily time series of rainfall/snowfall and maximum/minimum temperature.

The approach of building a community archive such as the LLNL-Reclamation-SCU downscaled climate projections derived from the WCRP's CMIP3 multimodel dataset, stored and served at the LLNL Green Data Oasis, should be adopted for any work involving intercomparisons and probabilistic downscaling techniques.

Pros

- Climate change data are provided at the spatial scale (e.g., regional, station) and timestep (daily, monthly) needed for water utility planning without further processing.
- Statistical downscaling development will target variables critical to water utility planning.
- This option is less expensive in terms of dollars and computational needs, compared to the other two downscaling investment options.
- A precedent exists for direct interaction between statistical downscaling and water resource communities.
- Ensembles of techniques and probabilistic methods can be applied in risk management tools.

Cons

- In regions where the climate change signal is incompletely simulated by changes in large-scale conditions, the completeness of climate change projections is subject to the same misrepresentation as GCMs, unless novel statistical downscaling techniques are successfully developed to represent regional changes. This is a high-risk, high-reward research topic.
- Improvements in representing regional climate dynamics must await evaluation of regional climate within GCM projections.

Availability

Evaluations could begin within a year of this report. The biggest return on investment would have as a target time period the evaluation of statistical downscaling techniques and development of a community archive in conjunction with the release of the CMIP5 dataset scheduled for 2011.

Estimate of costs

- An investment in research staff will be needed, similar to the level of funding from an external grants program: $5 million/year for 5–10 years.

- It may be necessary to invest in data archive resources for a particular institution: less than $1 million one-time investment.

4.3 Summary of Investment Options for Climate Models

Table 4.1 summarizes the investment options.

Table 4.1. Summary of investment options for climate models

Option	Pros	Cons	Time period	Costs
GCM investment options				
GCM-1. Develop and enhance GCM ensembles	Provide a rich set of scenarios Improve analysis of climate signal vs. model variability	More model runs require lower model resolution Storage may be limiting	2–7 years	\$3–5 M over five years for 100 km resolution \$10–30 M over five years for 50-km
GCM-2. Improve use of observations to constrain models' projections	Improve observations over time May be best hope for reducing uncertainties	May take decades Data assimilation technologically complex and computationally intensive	First results within 2 years Ocean modeling: 5–10 years Significant improvement may take longer	Research on statistical methods: \$2–5 M/yr GCM assimilation: \$2–\$10 M/yr per GCM Integration of data assimilation: \$2–10 M/yr
GCM-3. Improve tropical Pacific modeling	Might narrow precipitation projections for North America	Least chance of success Most costly option	5–15 years	Analysis: \$1–3 M/yr Modeling: \$5–10 M/yr
GCM-4. Evaluate decadal predictions	Provide more reliable projections for next few decades Enhance ability to integrate decadal variability with climate change	Predictive skill in forecasting these phenomena may be low Many methodological issues to be worked out regarding how to initialize the models	Projections could be available in 2 years	< \$1M/yr initially; more later if science makes progress

Table 4.1. Summary of investment options for climate models (cont.)

Option	Pros	Cons	Time period	Costs
Downscaling investment options				
DS-1. Develop regional and local climate change ensembles	Understand, characterize, and quantify uncertainty in regional climate projections Can enable probabilistic output Create archive of regional and local projections May trim to a less costly alternative Foster dialogue with water community	Most expensive DS option Requires high level of infrastructure, coordination, and maintenance Needs sustained investment over time	If begins within a year, results in 2–5 years	Infrastructure: \$5–10 M/yr Computing facility: \$10–15 M (one time cost) External grant program for scientific work \$10M per year for 5–10 years
DS-2. Develop RCM model components	Improve understanding of and reduce disparity in RCM simulations of regional processes, given accurate large-scale conditions Enable analysis of results from higher-resolution RCMs Foster dialogue with water community	Observation system may be inadequate for evaluation of high-resolution model output Output not necessarily at the scales needed by water utilities	Can begin within 1 year Many analyses done within 2–4 years	Research staff \$5 M/yr Computing facility: \$1–5 M Costs for observational system not estimated
DS-3. Develop statistical downscaling techniques	Produce a large number local climate projections of variables critical to water utilities Create archive of local projections. Can enable probabilistic output Foster dialogue with water community	Will reflect only large-scale changes; thus, probabilistic information will have incomplete representation of change	Can begin within 1 year Many analyses done within 2–4 years	Data archiving facility: less than \$1 M External grants program: \$5 M/yr for 5–10 years

k/yr = thousand per year; M/yr = million per year.

5. Using Climate Model Output for Water Resources Analysis

This chapter briefly addresses how climate model output can and should be used in the analysis of water resources. The topics discussed below are the appropriate use of model data for water analysis and how best to convert climate model output into hydrology.

5.1 What Are Appropriate Impact Assessment Uses for GCMs and RCMs, and How Could They Be Incorporated into Water Utility Planning Frameworks?

In general, the projections from climate models are more reliable for large areas and when averaged over many simulated years. In addition, temperature projections are more reliable than precipitation projections. So, the most reliable output from GCMs are long-term estimated changes in average global temperature. As we move to finer spatial or temporal resolution, the model projections become less reliable.

This is not to say that projections at less than a global scale are necessarily unreliable. Indeed, in recent years the quality and quantity of GCMs have improved to the extent that the IPCC now feels there is enough confidence to project long-term average changes in sub-continental climate. Christensen et al. (2007) conclude that in North America:

> … annual mean warming is *likely* to exceed the global mean warming in most areas. Seasonally, warming is *likely* to be largest in winter in northern regions and in summer in the southwest…. Maximum summer temperatures are *likely* to increase more than the average in the southwest. Annual mean precipitation is *very likely* to increase in … the northeast USA, and *likely* to decrease in the southwest…. Snow season length and snow depth are *very likely* to decrease in most of North America….” (p. 850)[1]

Projecting long-term average changes in climate at the sub-continental scale (e.g., the Southwest) is as far as the IPCC goes. Such projections are generally not at the scale water managers desire.

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1. “Likely” means the IPCC finds there is at least a two-thirds chance the projection is correct. “Very likely” means the IPCC finds there is at least a 90% chance the projection is correct.

The question being asked here is what are appropriate impact assessments using GCMs and RCMs. This question should be rephrased as "What are *relatively* appropriate impact assessment methods?" It could be argued that the climate models do not currently yield sufficient reliability to make forecasts of change in climate at the scale of river basins.

Yet, there are relative degrees of reliability. The basic principles stated above apply: the larger the area, the longer the time period, and the more reliable the model output. Projections over hundreds of miles are more reliable than projections over tens of miles. Projections of average annual change are more reliable than projections of average seasonal change, which are more reliable than projections of monthly change, which are more reliable than projections of sub-monthly change, and so on. And as noted above, projections of temperature change are more reliable than projections of change in precipitation.

Table 5.1 provides an analysis of a number of decisions on water resource management and the relative appropriateness of using climate model output. The decisions or issues regarding water resource management are split into three categories: water supply, flooding, and water quality. For each category, we give specific examples of outcomes water managers may be interested in, identify variables from climate models that can be used to estimate potential impacts, and give our judgment about the relative reliability of climate model output. Note that the reliability is stated as relative, not absolute. Even a rating of high should not be interpreted as having high confidence in the projections.

Table 5.1. Climate model variables and relative reliability for water resource analysis

Water management issue	Climate model variables	Relative reliability of climate model output
Water supply		
Long-term supplies – mean annual basin yield	Annual average temperature and precipitation	High on temperature Precipitation depends on geographic scale, higher at sub-continental scale RCM precipitation projections are more reliable than GCM projections
Long-term demand	Warm-season temperature and precipitation	Same as above
Shift in seasonality of runoff – snowmelt-dominated areas	Monthly temperature	Medium-High
Shift in seasonality of runoff – non-snowmelt-dominated areas	Seasonal precipitation	Medium-Low
Long-term supplies – variability in yield	Monthly temperature and precipitation	Medium-Low

Table 5.1. Climate model variables and relative reliability for water resource analysis (cont.)

Water management issue	Climate model variables	Relative reliability of climate model output
Flooding		
Seasonal floods	Winter and spring precipitation	Medium-Low
Major storms/cyclones	Frontal systems; cyclone formation and track	Low
Flash floods	Hourly precipitation in small geographic areas	Very low
Water quality		
Biological oxygen demand	Annual, seasonal, monthly air temperature (to estimate water temperature)	Medium-High
Dissolved oxygen	Annual, seasonal, monthly air temperature (to estimate water temperature)	Medium-High
Flow reduction	Annual, seasonal, monthly temperature, precipitation	Medium-High
Saline intrusion of groundwater	Sea level rise; annual temperature and precipitation	Medium-High
Algal bloom	Annual, seasonal, monthly temperature	Medium-Low
Turbidity	Daily, hourly precipitation intensity	Low
Cryptosporidium	Daily, hourly precipitation intensity	Low

5.2 What Are the Most Appropriate Methods for Converting GCM and Downscaled Data into Hydrologic Information Relevant to the Water Community?

Before addressing this question it is important to understand that in general, there is greater uncertainty about change in regional climate than there is about change in runoff *given a specific change in climate* (e.g., total water available, seasonality of runoff, change in peak and low flows, water quality). With regard to how climate change will affect water resources, the largest uncertainty is generally with the direction and magnitude of change in climate (e.g., how much will temperature increase, will precipitation increase or decrease and, if so, by how much and by when). While there is some uncertainty about runoff for a specific change in climate, the range of uncertainty in general is less than the range of uncertainty about climate change itself. This is not to trivialize or minimize the importance of understanding runoff or of comparing different runoff models that are widely used, but to note in general that reducing the range of uncertainty about change in climate at a regional scale would do more to reduce uncertainty about the effect of climate change on water resources than would reducing uncertainty about runoff itself.

GCMs and RCMs estimate runoff within grid cells. In general, it is better not to use such output for water resource planning. This is because the grid cells, particularly from GCMs, are generally larger that watersheds, and features such as rivers and lakes are typically not represented in climate models. An additional problem is that runoff is not routed between adjacent grid boxes. So, to estimate runoff, it is necessary to translate key meteorological variables, such as temperature and precipitation, into hydrology. This is typically done using hydrologic models. *The runoff model must be able to use climate variables as inputs in order to translate the change in climate simulated by a climate model to runoff.* To be sure, GCM output is rarely used to examine changes in runoff (a noted exception is Milly et al., 2005).[2]

There are two general types of runoff models: physically based models and statistical models. Physically based models try to simulate key physical processes of a system. In the case of runoff, they try to account for the fate and transport of water molecules in the system. For example, does the precipitation fall as rain or snow? If it falls as snow, does it stay in the snow pack, when does it melt, and does it ablate? If it falls as rain, does it run off the surface, or percolate below the surface? If it goes below the surface, does it go into an aquifer, does it go into a stream, or is it absorbed by vegetation? These processes modeled are based on what is known about physical and biological processes.

In contrast, a statistical model is essentially based on observed mathematical relationships. It may attempt to model the same processes but does so based on observations and mathematical relationships between variables.

An important factor in selecting the type of model for analysis of climate change impacts is how well we expect the models to perform in simulating conditions that may fall outside of observed conditions. The extent to which climate change will result in conditions outside of observations is itself debatable. It will depend in part not just on the range of observations in individual variables – e.g., is it hotter or drier than what has been observed before – but also the

2. Indeed, one application to be careful of is calibrating runoff to GCM or RCM simulations of current climate and using the relationship to estimate change in future runoff based on GCM or RCM projections of future climate. Among other problems, the relationships between GCMs and RCMs in simulation of current climate may contain biases which would not be corrected in a projection of future change.

combination of variables. For example, does the observed dataset capture persistent warming combined with decreases or increases in precipitation?

One of the concerns with statistical models is whether the quantitative relationships are credible when extrapolated beyond the dataset used to build the models. Climate change, for example, may create climates not observed or rarely observed. It is not clear if the statistical relationship based on observed climate in the statistical model will be maintained under a changed climate. The model may assume a linear relationship, which in reality could become nonlinear under climate change. In addition, factors such as land use are likely to change in the future resulting in change in the statistical relationships. Models based on current statistical relationships may not capture such changes. In theory, if physical models accurately simulate physical properties governing the system that is being modeled, then they should accurately simulate changes in the system even if conditions are outside of observations. In practice, this can be difficult to verify.

There are counterarguments. Physical models contain quantitative relationships that are based on observations. Thus, knowledge of how the physical system will behave under unobserved conditions may be limited. Statistical models tend to be easier to build and less expensive to run than physical models. Observations may contain a wide range of conditions and thus capture many potential changes in climate.

For utilities, the choice of model to estimate change in the quantity or quality of water resources may be complex. Producing more reliable results through the application of hydrologic models may be more expensive than using statistical models. The only choice available may be the use of statistical models. One hybrid approach is to use physical models to simulate a broad range of climate conditions that may be consistent with a range of climate model projections. Such information can be used to derive statistical relationships that can be used for further analysis.

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6. Concluding Thoughts

As we hope is implied in the opening "prayer" which introduces this report, the challenge in improving the science to adapt to climate change is understanding what is possible to do now with the information we currently have, what improvements in the science we can reasonably expect in coming years and decades, and what improvements in the science will not be possible for a long time, if ever. This report presents the views of several climate scientists and climate change impacts researchers on these matters.

First, we think that there are substantial opportunities to improve our understanding of regional climate change using information that is currently available and climate model runs that will be conducted for the IPCC AR5/CMIP5 exercises. Just as the IPCC AR4 made significant strides in making some projections on likely and very likely changes in climate for many regions using information from 23 GCMs and downscaling modeling results, we think the upcoming modeling experiments for IPCC AR5/CMIP5 can be used to further improve our knowledge on regional climate change. There are opportunities to develop larger climate projection ensembles for each CMIP5 GCM, study results across many GCMs, and conduct many more experiments with RCMs and statistical downscaling models. These will provide a richer dataset on regional projections than we currently have and should enable scientists to develop better information on regional climate change. One interesting opportunity may be to analyze the outputs of GCMs and downscaling methods at smaller scales than the sub-continental scales analyzed by the IPCC AR4 report. This could provide insight on climate change roughly at the scale of states. The IPCC AR5 and CMIP5 processes are starting to get underway. Any opportunity to influence the direction of the models needs to be seized quickly.

Second, we are confident that improvements will be made in climate change science modeling that will yield better understanding and projections of regional climate change. This will result from increased understanding of important factors affecting regional climate such as the tropical oceans as well as from improvements in the climate models. Improved computing power and physics will enable higher resolution GCMs and RCMs to be built. But, such improvements, particularly in model resolution, are not simple to develop. Higher resolution can require changes in how processes such as convective precipitation are modeled. Gains in one aspect of modeling can be offset by increased complications in other aspects of modeling. In sum, we think the science and models will continue to improve, but changes to the water resources community and other users will likely take a decade or more to be realized. Thus, promises of the next generation of modeling solving current limitations and concerns with precise and accurate projections of regional and local climate should be greeted with some healthy skepticism.

Third, given the evolving state of the science, what should decision-makers do about adaptation? With regard to climate change information, the choices on adaptation have often been framed too simply. On the one hand, some argue that we should only use historic information because there is too much uncertainty about regional climate change. Such an approach effectively assumes climate is stationary. But, this is wrong because the climate is changing. By ignoring the likelihood of continued change, such an assumption can lead to increased vulnerability. On the other hand, some argue for a "wait and see" approach with the assumption that soon a new generation of models will make dramatic improvements in precision and accuracy of climate forecasts. Based on what we know, this approach is also wrong. As we have indicated, we expect improvements over time, but not dramatic improvements. Thus, waiting will allow for *better* science to emerge, but we contend it will not allow for *perfect* science to emerge. A decade from now, there will still be uncertainties about regional and local climate change.

So, the challenge is how to work with what we have or what we can reasonably expect to have in coming years. The emphasis needs to be on decision analysis – how to make the best decisions *we can* about the management of water resources (or management of other climate sensitive resources). This means incorporating what we know about climate change, including what is known about consequences and likelihoods, into our decisions. Some decisions, which can be labeled as "no regrets," make sense regardless of climate change scenarios or even based on observed climate. There is no reason (at least from the perspective of climate change science) not to make such decisions now. Other decisions, such as making long-term investments in building of infrastructure or decisions on land use, ideally could benefit from a precise and accurate forecast of regional or even local climate change. Where precise forecasts are not available now and are not likely to be available in sufficient time to make such a decision, strategies such as incremental changes or hedging may be the best bet. Note that hedging may prove inadequate in the long run if climate change results in dramatic changes in water resources. Decision-makers will need to weigh the costs and consequences of potentially changing infrastructure too little versus changing it too much. As noted, Means et al. (2009) address decision-making options in more detail. The challenge is to use what is known about future climate change in creative ways to make the best decision we can.

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A. Information on the Scale of Models Used by Water Utilities

A.1 Denver Water

Platte and Colorado Simulation Model: PACSM is an integrated system of computer programs that simulate streamflows, reservoir operations, and water supply in the South Platte and Colorado River basins.

Spatial scale: The largest possible spatial scale that would benefit Denver Water's modeling spans the entire modeled region, including the Cameo gauge on the Colorado River to the Kearsey gauge on the South Platte River. This is roughly an oval shape, but covers approximately 10,000 mi^2. The optimal scale would be approximately 1 mi^2 because of significant topographic variation and uneven spacing between about 470 model nodes.

Time scale: Daily input data from all model nodes.

Input variables: Diversions, streamflows (historic naturalized), demand, bypasses, reservoir content, net evaporation (based on total precipitation and gross evaporation), and water rights. Precipitation data are used to calculate net reservoir evaporation. Municipal demand is based on temperature and precipitation data. Snow water equivalent data are used in forecasting operations.

Output variables: Streamflow.

Operation Spreadsheets and Extended Streamflow Prediction System (ESP): These spreadsheet-based "operating plans" use federal government provided data to forecast reservoir levels, inflows, outflows, tunnel diversions, etc. They also use ESP forecasts, which consist of daily natural streamflow hydrographs based on current conditions in the basin and weather scenarios from the past. Each hydrograph assumes the current conditions as a starting point with each of the 27 years of weather run through a hydrologic model to create the hydrographs. If GCM output could be used to adjust the 27 years of weather data to account for climate change, the information would be useful.

Spatial scale: The largest possible spatial scale that would benefit Denver Water's modeling spans the entire modeled region, basically the South Platte basin through the South Platte gauge, approximately 2,250 mi^2. The optimal scale here would be the shortest distance between Denver Water's dams and storage areas, which is approximately 10 miles.

Time scale: The spreadsheets forecast 3–15 months into the future. The ESP forecasts run on daily streamflow hydrographs.

Input variables: Snow water equivalent, snow cover, precipitation, snow melt, temperature, and evapotranspiration. More variables can be used, such as wind speed, etc.

Output variables: Inflows, outflows, and storage levels for all major reservoirs.

Demand: This is an activity that was described in some detail in the materials received, but without a “big picture” description of where this activity falls in Denver Water’s overall planning efforts.

Spatial scale: The Denver Water service area, approximately 330 mi^2.

Time scale: Project annual demand with seasonal (summer and winter) components. Use average daily maximum temperature and total precipitation for each bimonthly billing period (January–February, March–April, etc.).

Input variables: A single temperature, precipitation, etc., value for the entire supply area, averaged from several area weather stations’ data.

Output variables: Water quantity demand.

A.2 New York City Department of Environmental Protection

OASIS: The entire New York City water supply can be simulated using the OASIS system operating (mass balance) model. In its present form, OASIS simulates water quantity and flows, but does not consider issues of water quality. Work is underway to integrate OASIS with CE Qual W2 (see Reservoir models, below).

Spatial scale: The water supply mass balancing model operates on the scale of the water supply region, which extends up to 125 miles northwest of downtown Manhattan and is approximately 5,100 km^2 in size.

Time scale: Daily.

Input variables: Watershed/streamflow modeling is driven by air temperature and precipitation data (but dewpoint and solar radiation are also important factors). Wind and solar radiation will become increasingly important as evaporation increases. For the New York City model, OASIS inputs include reservoir inflows, reservoir and conveyance characteristics and constraints, supply and storage goals (water demands both within New York City and in the northern supply area), and operating rules.

Output variables: Streamflow.

Variable Source Loading Function model: A variant of the GWLF (Generalized Watershed Loading Function) model, VSLF simulates water quality and quantity, including dissolved and particulate nutrient loads at daily timescales.

Spatial scale: VSLF models have been developed for major reservoir watersheds.

Time scale: Daily.

Input variables: VSLF is driven by daily time series of measured precipitation and air temperature, spatially averaged over the watershed; and optionally daily solar radiation and relative humidity when the Priestley-Taylor potential evapotranspiration algorithm is used.

Output variables: Streamflow, evapotranspiration, potential evapotranspiration, total dissolved phosphorus, total dissolved nitrogen, particulate phosphorus, and total suspended sediments.

Reservoir models: NYCDEP routinely uses two classes of reservoir models. One-dimensional (1-D) models are used to examine issues related to nutrient loading and eutrophication. CE Qual W2, a two-dimensional (2-D) reservoir model, is typically used to simulate the transport of turbidity through Catskill system reservoirs.

Spatial scale: Reservoir water quality modeling is conducted on the scale of the component watersheds (hundreds of square miles). For turbidity modeling in particular, 25 km^2 grid cells would be optimal in order to better understand the impacts of intense precipitation events.

Time scale: 1–6-month forecasts.

Input variables: Reservoir water quality modeling is driven by air temperature, dewpoint, solar radiation, wind speed, and direction. The 1-D models are driven by 35 years of meteorological data, reservoir operations data, and VSLF-derived nutrient loads. The 2-D model is driven by gauged tributary flows, operations data, and stream temperature measured as a function of air temperature.

Output variables: Nutrient loading and eutrophication, transport of turbidity.

A.3 Portland Water Bureau

Distributed Hydrology, Soil-Vegetation Model: DHSVM is a subregional hydrology model.

Spatial scale: PWB's watershed is approximately 92,000 acres (370 km^2) in size.

Time scale: Unclear from the materials we received.

Input variables: DHSVM is driven by temperature and precipitation, with information in the small grid sizes about vegetation height, soil depth, elevation, slope, and slope aspect. While PWB could use a large amount of temperature and precipitation information for this model, it has tended to use a single National Weather Service station at the Portland Airport. For the climate study mentioned above, PWB used monthly degree change in temperature and monthly percentage change in precipitation.

Output variables: Daily streamflow values.

Supply and Transmission Model/Water Evaluation and Planning model: Portland uses two mass balance models, based on the Stella platform (STM) and the WEAP platform. More information was available on STM than on Portland's use of WEAP. Consequently, the information below refers to STM. The STM and its use with the Bureau are described in Palmer et al. (2000).

Spatial scale: Covers PWB's entire service area, with nodes for all major wholesale customers.

Time scale: Daily information or rolling seven-day averages for summer supply planning and PWB's water demand model.

Input variables: Streamflows calculated from DHSVM.

Output variables: Annual minimum storage, groundwater pumped, length of drawdown, etc.

A.4 San Francisco Public Utilities Commission

Hetch Hetchy/Local Simulation Model: This is a water supply planning (mass balance) model that simulates SFPUC's operation of San Francisco's Hetch Hetchy facilities, the Don Pedro Project, and the Bay Area reservoir, conveyance, and treatment system. This model includes a watershed runoff forecasting routine for water supply and power generation allocations and operations of other Tuolumne Rive stakeholders. The HH/LSM analyzes system operations based on historic hydrology (1920–2002), including actual hydrological sequences and events, and the model allows the SFPUC to predict the consequences of hydrologic changes to the system's facilities and/or operations both for multiple year drought and long-term average conditions. A Parsons/CH2MHill report stated, "[HH/LSM] can also be used to assess benefits and impacts to SFPUC regional water system long-term delivery reliability based on…changing hydrologic conditions." The model itself, however, does not use climatological variables directly as inputs; instead, watershed runoffs are a model input to HH/LSM. Integrating climate models would require runoff analyses outside of the HH/LSM platform to estimate climate change effects on system facilities and operations using HH/LSM for utility planning efforts.

Spatial scale: Each of the three watershed areas under consideration: the Tuolumne River system, the Alameda Creek system and the Peninsula watershed system. Hetch Hetchy Reservoir, part of the Tuolumne River system is fed by a 459-mi^2 (1,190-km^2) watershed. This is the largest watershed in the system. Alameda Creek system watersheds total approximately 175 mi^2 (for two reservoirs). Peninsula system watersheds total approximately 33 mi^2 (for three reservoirs).

Time scale: All variables have a monthly timestep.

Input variables: Unimpaired runoff at all reservoirs and some other locations, accumulated precipitation at Hetch Hetchy, empirically calculated monthly evaporation rates based on reservoir surface area without using temperature values.

Output variables: Water in reservoir storage, releases and stream flows, water deliveries, and other parameters associated with the system's reservoirs, conveyance facilities, and treatment plants. The model provides information representing monthly volumes of water, although certain parameters have been converted to flow rates.

A.5 Seattle Public Utilities

Seattle Forecast Model: SEAFM is a hydrology (rainfall-runoff) model used in operational forecasting and operations planning (also making it an operational model). This model uses meteorological data as inputs, and could therefore use GCM outputs. SPU uses other tools, such as spreadsheet models, to support operational planning as well. This model has been updated to HFAM and is known as HFAMII; this model has more, smaller land segments compared to SEAFM.

Spatial scale: The largest area that could be modeled is 203 km^2, as this represents the total area draining to Masonry Dam on the Cedar River. Depending on which version of this model is used, the total drainage area is divided into approximately 30 or 300 land segments of differing shapes and sizes. The land segments range in size from 27 km^2 to 0.021 km^2.

Time scale: The model provides projections of days or weeks into the future for flood management, through the end of the year for seasonal planning, and can run continuously started in water year 1929.

Input variables: This model uses meteorological/weather station data as inputs.

Algorithms are used to take data from one to eleven stations for each land segment. Specifically, the model requires hourly precipitation (also uses daily and six-hourly precipitation from some stations to fill in data gaps), and minimum and maximum daily air temperatures (although some data sites have finer temporal scales, e.g., hourly). Assumptions are made about wind speed, solar radiation, and lapse rates.

Output variables: Outputs from the model include soil moisture, snow water equivalent, streamflows, and reservoir levels.

Conjunctive Use Evaluation (CUE): CUE is a water system model used in water supply planning. This model uses unregulated inflows for the Cedar and Tolt River systems generated outside the model as inputs, and therefore cannot use climate model outputs directly. While current policy has CUE using inflow data generated outside of SEAFM, it is technically possible to use the streamflow output from SEAFM as an input into CUE. In this way, it may be possible to use climate model outputs as inputs for both of SPU’s models.

Spatial scale: CUE models drainages ranging from 13.8 km^2 to 203 km^2.

Time scale: Weekly-averaged data for inflows.

Input variables: CUE, by official procedure, uses an unregulated inflow dataset generated outside the model, but it can also use inflows generated by SEAFM.

B. Statistical Downscaling Techniques

B.1 Traditional Typology of Statistical Downscaling Techniques

Statistical downscaling techniques are usually developed for specific applications. The number of techniques is limited, therefore, only by the number of creative model developers. Thus far, many reviews of statistical downscaling techniques have placed these techniques into the following six categories:

1. Change factors

Change factors compute either a difference or a percentage change between output from GCM contemporary and future climate simulations. The change factors are applied to station data. They, therefore, preserve the sequence of weather events in historical station observations.

2. Adjustments to moments of probability distributions

Moments are measures of probability distributions, such as mean, standard deviation, and asymmetry about the mean (skewness). Similar to change factors, some measure is devised that relates the probability density function moments of GCM contemporary climate simulations and station data. The measure is then applied to the GCM future climate projection. One adjustment that is critical to downscaling activities is bias correction, which is an adjustment to the mean of the probability distribution to match that of observations. This removes the influence of systematic errors in downscaled GCM output.

3. Adjustments to probability distributions

Adjustments to probability distributions (sometimes called quantile matching or percentile matching) involve building histograms of variables for both GCM contemporary climate simulations and station data. At predefined histogram percentiles, the value of the GCM data is matched to the station. For example, the 75th percentile station of station monthly average temperature may be 25°C; whereas, the GCM contemporary climate value may be 21°C. The GCM 75th percentile value of 21°C is simply replaced with the station value of 25°C. The GCM future climate projection is first ranked within the GCM contemporary climate histogram. Then, the percentile matching technique is applied to it. Detrending of GCM future climate projections may be necessary before percentile matching is applied.

4. Regression

Regression approaches use a weighted combination of variables from the GCM contemporary climate simulation as predictors for the station data. Regression may represent either linear or nonlinear relationships (e.g., artificial neural networks) and may include multiple predictors, such as fields of data.

5. Analogue matching or weather classification techniques

Weather classification methods group days into a finite number of discrete weather types. Recent advances use methods, such as constructed analogues (Maurer and Hidalgo, 2007), that expand the universe of weather types by piecing together portions of different weather events. Weather types are defined typically by selecting most-like conditions based upon the assessment of a human expert or a statistical measure or combinations thereof. Station observations are assigned to the weather type. GCM projections are then placed into the categories and assigned station values by some weighting applied to a combination of like conditions.

6. Stochastic weather generators

Weather generators are stochastic models that generate time series of weather data by random sampling from conditional probability distributions of station observations that are conditioned upon large-scale information from GCM contemporary climate simulations. Weather generators replicate the statistical attributes of a local climate, but not observed sequences of events. The large-scale information in GCM future climate simulations is then used as the conditioning agent to generate new time series.

B.2 Details of Three Statistical Downscaling Techniques in Use by WUCA Members

Three statistical downscaling techniques in use by WUCA members are described in detail below in order to illustrate how contemporary techniques fit within and have expanded the traditional typology of statistical downscaling techniques described in Section B.1. A detailed review of all techniques in use by water utilities is outside the scope of this report. The three techniques described below were deemed illustrative due to either their ubiquity or direct applicability to daily data.

An adaptation to the change factor methodology (Method 1 in Section B.1) that reduces the linearity assumption of its traditional usage has been and is being used by NYCDEP and others (Andréasson et al., 2004). An advantage of the change factor method is that the historical meteorological pattern found in the station data remains as a baseline reference and this enables synchronization of the history of system operations that occurred in response to historical meteorology with meteorological events in the future climate scenario. The disadvantage of this approach is that the method relies on the historical time series to order the occurrence of events and fixes the event arrival times, and as a result, differing future climate scenarios will not be truly independent datasets. In its simpler form, a seasonal or monthly factor is applied equally to each day within a season (month) of the station data to produce a scenario with the same meteorological pattern as the historical data but with adjustment to the seasonal mean values. When factors are calculated and applied to sub-ranges of the probability distribution of station data, nonlinear changes in distributions of meteorological variables are introduced to emulate changes in the intensity of extreme events. Even more sophisticated applications may utilize nonlinear or discontinuous functions to adjust the distributions of storm and inter-storm period lengths while maintaining a morphological connection to the original historical station data.

The bias-correction and spatial downscaling (BCSD) method, introduced in Wood et al. (2004), combines change factors (Method 1 in Section B.1), quantile mapping (Method 3 in Section B.1), and stochastic weather generators (Method 6 in Section B.1). In this method, monthly precipitation and temperature output from a GCM are downscaled, and daily data are created by applying a stochastic weather generator to the monthly data. In this way, the BCSD method does not account for changes in the statistics of climate variability at scales less than monthly that may be projected by a GCM, and is not expected to exhibit skill at projecting statistics of daily extremes above simply assuming climatological daily variability. The BCSD method first aggregates monthly observations to the grid of the GCM. The technique uses a quantile-based mapping of the probability density functions for the monthly GCM precipitation and temperature to remove GCM biases. This same mapping is applied to the future GCM simulations. The final steps compute change factors between the GCM baseline and future simulations, interpolate the change factors to the high-resolution grid of observations, and apply the change factors to the observational climatology. Unlike the traditional use of change factors, this approach does not use the sequence of observed weather events. The advantage of this approach is that the mean and variability of a GCM may evolve in accordance with the GCM simulation, while preserving all statistical moments of the observations for the base period.

The BCSD method is one of a small number of statistical downscaling methods that have been applied to output from both GCM and RCM simulations. Results indicate raw output from GCMs and RCMs produces a poor representation of hydrology for all time horizons (daily, seasonal, annual) in the Northwest. When BCSD is applied, the hydrology is reasonable, and the climate change sensitivity is larger when using RCM compared to GCM data as input to BCSD.

The constructed analogue (CA) approach, described in Hidalgo et al. (2008), blends analogue techniques (Method 5 in Section B.1) and linear regression functions (Method 4 in Section B.1) to produce a larger universe of analogues. The technique is applied to daily weather patterns. The pattern to be downscaled is constructed from a linear combination of previously observed coarse-scale patterns that are most similar to the target pattern. Thus, a single pattern is not used as the analogue. Instead, multiple analogues are selected, and only the pieces that best fit the pattern to be downscaled are used. The linear regression coefficients are then applied to the high-resolution patterns that are associated with the observed coarse-scale patterns. The advantages of this method are that never-before-observed patterns are generated by patching together many observed patterns, thereby expanding the library of analogues, and daily sequences of weather are generated that reflect the GCM's daily weather evolution. The disadvantage is that the sequencing of daily weather from the GCM is retained so that biases in GCM variance are reconstructed in the downscaled data.

C. Characteristics of Reliable Statistical Downscaling Practices

The reliability of regional climate projections made with statistical downscaling techniques may be evaluated by means of four climate simulations: baseline climate simulation, alternative baseline climate simulation, contemporary climate simulation, and future climate projection. For statistical downscaling techniques, the alternative baseline climate simulation may be obtained by one of the following approaches: (1) calibrate the statistical model on a “cold” period and validate it on a “warm” period, and vice versa; and (2) calibrate the statistical model in one region and apply it (without re-calibration) in a warmer region with equally simple topography.

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A benefit of the European intercomparison of statistical downscaling techniques called STARDEX (STAtistical and Regional dynamical Downscaling of EXtremes) is the development of criteria for evaluation of the robustness of statistical downscaling methods that can be applied as part of an analysis of the four climate simulations described above. The robustness criteria are listed below.

- *Strength and stability*: Can strong relationships between large-scale and station data be identified? Are these relationships physically interpretable? If different methods or time periods are used for selection of large-scale conditions, are similar sets of station data obtained? Is the strength of the large-scale and station data relationship or performance of the model sensitive to changes in calibration or validation period? Is the model performance sensitive to other changes, such as the number of and types of large-scale conditions?

- *Stationarity*: Minimize the possibility that due to climate change the empirical mathematical relationships will be invalid by the incorporation of large-scale conditions that are expected to change based on literature review and theoretical considerations. Assess whether direction and magnitude of observed trends in large-scale conditions, together with low-frequency variability, are reproduced by the statistical model via cross-validation techniques. Assess whether GCM future climate projections of changes in large-sale conditions lie outside the range of variability observed over the calibration and validation periods.

- *Uniformity of performance*: Assess whether measures of model performance are similar across stations, regions, seasons, variables, and indices of extremes, such as a drought index.

- *Reliability of simulation of large-scale conditions*: Comparison of baseline climate simulation and contemporary climate simulation should take into consideration raw values, derived indices (such as a drought index), spatial patterns, temporal trends, frequency of events, persistence, day-to-day transitions, and circulation types. Is the performance of the model for the baseline simulation degraded when large-scale conditions are taken from the GCM output, rather than from observations or observational proxy datasets?

D. Characteristics of Reliable Dynamical Downscaling Practices

The reliability of regional climate projections made with regional climate models (RCMs) may be evaluated by means of four climate simulations: baseline climate simulation, alternative baseline climate simulation, contemporary climate simulation, and future climate projection. Baseline climate simulations are sometimes called perfect boundary conditions, because the observational or proxy observational dataset presumably represents an input source that is relatively free of errors compared with GCM data. Also, the contemporary climate simulation is sometime called the "control" simulation. The alternative baseline climate simulation may be obtained by choosing a domain in another continent, preferably one that may have characteristics similar to the anticipated effects of climate change in the domain for the baseline climate simulation. Some considerations to keep in mind when evaluating the reliability of RCM simulations follow.

- *Reliability of process simulation:* What are the key processes that affect the variable(s) of interest, and are these processes explicitly simulated by RCMs? Does evaluation of baseline climate simulations for the variable(s) of interest show sensitivity to domain boundary location, alternative combinations of parameterizations, or grid spacing? Does this sensitivity create variability in the variable(s) of interest that is larger than their observed range? Are the large-scale conditions of the dataset used as boundary conditions replicated in the interior RCM domain?

- *Sensitivity to climate variability:* Is the reliability of processes different for extreme seasonal conditions, e.g., warm winters versus cold winters? Are the variable(s) of interest considerably degraded in the alternative baseline simulation?

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E. Approximate Spatial Scale Needed to Resolve Selected Climate Phenomena Related to Ocean Processes

These were selected to illustrate the main benefits for of different resolutions in improving global climate simulations.

Table E.1. Approximate spatial scale needed to resolve selected climate phenomena in the ocean component model

Ocean model	Phenomenon	Why important for climate and water resources
10-deg (3 deg)	Major surface ocean current systems, ocean surface temperature	Essential for global ocean temperature, and latitude gradient and their influence on continental temperature; ocean heat uptake
3-deg (min) 1-deg	Equatorial Ocean Thermocline Displacements (“Waves”)	Essential for Tropical ocean climate, seasonal cycle, and ENSO, and related effects on North American climate
1/3 degree (min) 1/10 degree (resolved)	Ocean mesoscale eddies	No need for “eddy diffusion” parameterization; poleward movement of heat; midlatitude ocean temperatures; details of Gulf Stream and other ocean currents; connection to water resources; changes in East Coast climate/sea levels
1/6 degree	Tropical instability waves; equatorial undercurrent	Movement of heat in the Tropical Pacific; Tropical ocean temperatures and their influence on North American climate

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Denver Water • The Metropolitan Water District of Southern California
New York City Department of Environmental Protection • Portland Water Bureau • San Diego County Water Authority
San Francisco Public Utilities Commission • Seattle Public Utilities • Southern Nevada Water Authority

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