## Contents



## 1. Introduction

This primer was prepared by the Southwest Climate Science Center as a companion to the Southwest Climate and Environmental Information Collaborative (SCENIC, www.wrcc.dri.edu/csc/scenic) to assist users of SCENIC in understanding and applying climate data. Section 2 defines climate and weather data, describes climate variables, and discusses trade-offs among different types of climate data. Section 3 addresses global climate models (GCMs) and the emissions scenarios they reflect. Section 4 introduces the two primary methods of downscaling GCM projections, statistical and dynamical, and summarizes common methods for statistical downscaling. Section 5 discusses the process of selecting a GCM or ensemble of GCMs for a particular application.

## 2. Climate data

Climate is the statistics of weather. Weather refers to atmospheric phenomena or patterns over minutes to days, whereas climate refers to trends in weather over weeks or longer.

Climate data include diverse meteorological variables, some of which have been measured for more than a century. Many of these data originally were used to forecast weather, but the data also are useful for analyses of past climate and projections of future climate. Most meteorological variables can be used to study both weather and climate, although longer records are required for climate studies.

## Climate variables

The following weather variables commonly are measured and aggregated over time to characterize climate.

- Precipitation. Precipitation can be expressed as a total or by type (e.g., snow or rain).
- Temperature. Temperature can be measured at different altitudes (e.g., atmospheric, ground level), above different surfaces (e.g., land, sea), and at different times of the day.
- Wind. Common measurements of wind are its speed, direction, and duration.
- Cloud cover and type
- Humidity

Additional variables are relevant to the expression of weather and climate.

- Albedo, the reflectance of Earth's surface.
- Topography and bathymetry, which refer to the shape and features of Earth's surface, including the ocean floor.
- Ice and snow cover. The extent of Earth's surface that is covered by ice and snow affects albedo.
- Vegetation cover
- Soil moisture

The precision, accuracy, and spatial and temporal scale of measurements differ among climate variables. Understanding how a climate variable is measured allows one to interpret its utility for a particular application. Some variables (e.g., temperature) are relatively easy to measure and interpolate among locations. Therefore, precise, fine-resolution data on these variables are available. Data on variables that are relatively difficult to measure (e.g., wind, humidity, soil moisture) or that are easy to measure but difficult to interpolate (e.g., precipitation) may be less precise or may be accurate only at coarse resolution.

Meteorological data can be presented in multiple ways. Raw data, often in the form of measurements from instruments at point locations, are the most informative, but voluminous raw data can be difficult to manage and interpret. Summary data, such as means or ranges over time or space, may be useful in situations where the finer resolution of raw data is not needed. Data also can be provided or summarized on the basis of application-specific criteria, such as values above or below a given threshold. Most climate data are either measured by on-site instruments (in situ data) or measured by sensors on satellites.

### Climate normals

Climate normals, also called 30-year normals, are 30-year averages of climate variables. Climate normals are produced once every ten years by the National Centers for Environmental Information. The 1981–2010 U.S. Climate Normals are the most recent product. The data include daily and monthly temperature, precipitation, precipitation falling as snow, heating and cooling degree days, dates of frost and freeze, and growing degree days. Climate normals are based on observations at approximately 9,800 stations operated by the National Oceanographic and Atmospheric Administration's National Weather Service.

### Selection of climate data

Spatial continuity, scale, and data type are among the criteria to consider in selecting climate data for a particular application.

Station data are spatially discontinuous measurements taken at weather stations. These data usually are precise, but the density of weather stations in a given region may be low. The density of locations also tends to be correlated with human population density. Therefore, the density of weather stations generally is greater in valleys than mountains. Gridded data are spatially continuous and are derived statistically for a fixed area on the basis of station data. For example, if a grid cell is 100 kilometers on each side and five weather stations are located within the cell, the value of a climate variable for that cell may be a summary measure of the values from the five weather stations.

The two elements of scale are extent and resolution (also called grain). Extent is the full geographic area (space) or duration (time) over which a variable is measured. For example, a data set may cover the conterminous United States over the period 1950-2015. Spatial resolution refers to the smallest measurable unit (e.g., square meters, square kilometers). Temporal resolution refers to the smallest measurable time interval, or to the frequency with which observations are made or at which they are averaged (e.g., hourly, daily, monthly, annual).

There are two main types of climate data: observations and output from models. Observed (also called historical) data are those that were measured directly at known times and locations. Modeled data are estimates of climate variables derived from a proxy (e.g., tree rings or ice cores) or from one or more algorithms. Data can be modeled for any time period, including time periods for which observed data exist. Modeled data can be used to reconstruct prehistorical climate, to test whether a climate model is accurate by comparing the modeled data against observations, and to project future climate (often through the use of global climate models). There are trade-offs between observed and modeled data. The accuracy of observations may be compromised by miscalibrated instruments, changes in the environment around a station, data gaps or poor spatial coverage, and reporting or recording errors. Modeled data can have systematic biases or misrepresent physical processes.

## 3. Global Climate Models

Climate is an emergent product of Earth's orbit, volcanic activity, atmospheric gases, and energy transfers among air, water, and land. Climate models include equations that represent the physical drivers of climate sufficiently to make useful statistical predictions at global extents and over long time periods. Solving the equations requires substantial amounts of observed or modeled data.

Climate models generally are constructed at the global extent. Local changes in climate result from interactions among local factors (e.g., topography, atmospheric circulation patterns, cloud cover) and the global climate. Climate models partition Earth's surface, atmosphere, and oceans into grid cells, rectangles that are the finest resolution for model inputs and projections. Grid cells are both arranged horizontally across Earth's surface and stacked vertically to estimate values of climate variables at different altitudes or ocean depths. Because running global models requires ample computing capacity and time, the grid cells usually are quite large. The centers of grid cells typically are separated by 1–2.5 degrees of latitude and longitude. One degree of latitude and longitude in California equals approximately 100 kilometers (62 miles), or about the distance from Sacramento to Berkeley, whereas 2.5 degrees encompasses San Francisco to Lake Tahoe, and includes two mountain ranges and the Central Valley. At 2.5-degree resolution, no river catchment in California spans more than a few grid cells, and most river catchments are much smaller than one grid cell.

Global climate models (GCMs) are simulation models, the outputs of which are used to investigate possible future climate, including future climate variability and change (e.g., Barsugli et al 2009, Taylor et al. 2012, Stocker et al. 2013). Observations of past climate and indicators of past climate, such as tree rings, are useful for inferring potential future ranges of variation in climate and ranges of values of climate variables. However, GCMs are the most common means of quantitatively projecting future climate. GCMs represent relations among the atmosphere, oceans, and land. Drivers of climate variability and change in GCMs, sometimes called *forcings*, include fluctuations in solar energy, volcanic activity, atmospheric concentrations of greenhouse gases that are produced by human activities (emissions), aerosols, and land-use changes (Stocker et al. 2013). GCMs are run prospectively (e.g., over the 21st century) to explore how climate may change. These projections of future climate are not predictions or forecasts, partly because they depend on assumptions of how people will act in the future (e.g., Knutti 2008, Schmidt and Sherwood 2014). GCMs also are run retrospectively over the past several decades. Modeled historical climate provides a standardized basis for comparison with projected climate. Additionally, comparison of the historical GCM runs with observed global and regional climate allow for estimation of model accuracy. Nevertheless, the GCMs that most accurately represent historical climate are not necessarily the most useful for predicting future climate. Modeled historical climate never will perfectly match observed historical climate. The accuracy of GCMs is affected by the accuracy of their inputs and of projections of human activity and how it affects Earth.

Climate projections, including regional projections and downscales (see below), are affected by multiple forms of uncertainty (Hawkins and Sutton 2011), such as uncertainties in climate forcings (including clouds and particulates), uncertainties in how accurately the model represents the true climate system (Tebaldi et al. 2005), natural variability in climate (Deser et al. 2012), and observational errors (Pierce et al. 2013). These projections of future climate are not predictions or forecasts (e.g., Knutti 2008). Climate projections present ranges of possible future values of climate variables given assumptions or scenarios about society and technology in the future, whereas forecasts predict future values and associated confidence levels given past and current values. Different climate projections make different assumptions about future emissions, levels of population growth, technological advances, and so forth.

## Creation of global climate models

The first step in creating a climate projection with a GCM is to select a social and economic projection for Earth that reflects estimates of human population growth, energy demand, and methods of producing energy over the temporal extent of the model. The second step is to create emissions scenarios that are based on these projections. These emissions scenarios estimate the volume of greenhouse gases present in the atmosphere over time. The third step is to incorporate the emissions scenarios into a model that projects future values of climate variables.

The output of a GCM varies in part as a function of the representative concentration pathway (RCP) that is chosen for a particular model run. RCPs are standardized scenarios of future emissions given different assumptions about land use, population growth, and technology. RCPs are expressed as the radiative imbalance (incoming solar radiation minus outgoing energy radiated to space), in Watts per square meter of Earth’s surface, between projected emissions in 2100 and preindustrial emissions. Four RCPs are used in most GCMs: 2.6, 4.5, 6.6, and 8.5. The number reflects the difference in $W/m^2$ between the two time periods. For example, RCP 2.6 represents an increase of 2.6 $W/m^2$ from the preindustrial era to 2100. RCPs were introduced in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) (Taylor et al. 2012, Stocker et al. 2013). The most commonly used projections of low and high emissions are RCP 4.5 and RCP 8.5, respectively, although RCP 8.5 still may underestimate the radiative imbalance in 2100. Current emissions are above the RCP 8.5 level (Peters et al. 2013).

## 4. Downscaling

The spatial resolution of GCM grid cells is too coarse for most applications to resource management. Therefore, methods for downscaling—deriving fine-resolution estimates from a coarse-resolution model—have been developed.

Statistical downscaling uses derived statistical relations between historical, fine-resolution observations of weather (e.g., daily) or climate (e.g., monthly) and coarse-resolution GCM outputs to increase the spatial resolution of climate projections. Dynamical downscaling increases the resolution of climate projections by applying numerical, three-dimensional representations of atmospheric hydrodynamics and thermodynamics. These representations are similar to those used in GCMs, but have finer resolution and are run over a region rather than the globe. Both statistical and dynamical methods downscale data and uncertainties from GCMs. However, statistical methods attempt to correct GCM biases under the assumption that historical biases also will be applicable in the future (the stationarity assumption).

The computational requirements for statistical downscaling are lower than those for dynamical downscaling. Products from statistical downscaling of a large number of climate-change scenarios from diverse GCMs are readily available. Statistical downscaling is feasible to apply to the outputs of an ensemble of GCMs, whereas application of dynamical downscaling to many GCMs can be prohibitively expensive. Projecting climate change on the basis of an ensemble of GCMs generally is preferable to making projections on the basis of a single GCM because errors from different models tend to cancel out (Pierce et al. 2009).

### Methods of statistical downscaling

Delta method. The delta method, also called the delta factor or change factor method, is the simplest downscaling method. The delta method adds a model-projected future change to finer-resolution historical data (e.g., from PRISM (PRISM climate group 2004)) to project the future climate. For example, if a GCM projects an average increase in temperature of 3°C in 50 years, then historically observed temperatures are increased by 3°C to simulate weather patterns 50 years in the future.

Weather typing. The weather typing method derives relations between atmospheric circulation and local weather classes, and then applies these relations to GCM outputs to generate finer-resolution projections. This approach is useful because GCMs represent patterns over large spatial extents more accurately than patterns over small extents. Weather typing is based on characterization of different patterns, such as the number of consecutive dry days or the amount of precipitation on wet days during a dry winter in California, in observed weather data. The weather typing method uses cluster analysis to classify the daily values of the target climate variable over a given time period. Then, for each class, the method identifies GCM circulation patterns that correspond to the observed weather on a given day in a grid cell. This process also builds a library of classes, allowing all observations in each class on each day in the historical record to be compared to a given circulation pattern. The library can be used to convert GCM projections of future atmospheric circulation patterns into finer-scale projections of local weather.

Bias-correction with spatial disaggregation (BCSD). The BCSD method first removes systematic model biases through the process of quantile mapping. Quantile mapping converts every modeled value of a given climate variable into to the corresponding percentile in the model's historical distribution of all values. The final bias-corrected value of the climate variable is the observed value at the same percentile. For example, if the modeled median (50th percentile) value of temperature in a given grid cell is 20°C, but the observed median value in that grid cell is 18°C, then all model-generated values of 20°C are changed to 18°C. In the second step of the BCSD method, spatial disaggregation, a month of daily observations of the climate variable is selected, and the modeled mean value for that month is adjusted to equal the mean observed value for the month. For example, say precipitation during the modeled month was 12 cm, and precipitation during the observed month was 10 cm. The BCSD-generated sequence of daily values will equal the observed sequence of daily values multiplied by 1.2. Because the BCSD method derives modeled sequences of daily values from observed sequences, it generates realistic daily sequences. However, the BCSD method cannot simulate future changes in sequences of daily values.

### *Methods highlight: localized analog statistical downscaling*

Constructed-analog methods such as bias correction and constructed analogs (BCCA; Maurer et al. 2010), multivariate adaptive constructed analogs (MACA; Abatzoglou and Brown 2012), and localized analog statistical downscaling (LOCA; Pierce et al. 2013) statistically downscale a GCM day by choosing about 30 historical days (analog days) that are similar to the modeled day. The LOCA then combines the analog days to best match the modeled day. The BCCA and MACA calculated a weighted sum of the 30 analog days, which reduces extreme values of climate variables and increases spatial coherence. LOCA was developed primarily to reduce bias in simulation of mean and especially of extreme downscaled precipitation and temperature. LOCA selects one of the 30 analog days for application each small region of the downscaled output; thus, the selected analog day varies across the domain. Additionally, Pierce et al. (2013)

developed a new bias-correction method that, unlike quantile mapping, preserves the original GCM-projected future climate, and adjusts GCM simulations according to their differences from historical observed climate over a smoothed temporal-frequency continuum from decadal to daily. This correction increases the fidelity of the simulated fluctuations of precipitation and temperature over the range of temporal resolutions, and preserves GCM-level changes in precipitation and temperature in the bias-corrected result. All constructed-analog methods assume that the current relation between coarse-resolution average values and fine-resolution values of climate variables does not change in the future. This assumption may be violated, for example if future warming causes complete loss of snow cover in some regions.

### Dynamical downscaling

Dynamical downscaling uses a GCM to drive a regional climate model, which is similar to a weather-prediction model. The grid cells in regional climate models are smaller than those in GCMs, usually 12 to 50 kilometers on each side. The fine-resolution projections from dynamical downscaled models may be more accurate than those from statistically downscaled models because they directly incorporate fine-resolution data rather than statistically approximating fine-resolution data from coarse-resolution data. However, dynamically downscaled data still may have substantial biases. Moreover, given the computational requirements, dynamical downscaling currently is feasible only for small spatial and temporal extents and for application to the output of a single GCM. Statistical downscaling is more feasible for applications at relatively large extents (e.g., at the continental level over decades) or for application to the outputs of ensembles of GCMs. Dynamical downscaling is preferable to statistical downscaling when observational data are quite limited.

## 5. Guidelines for selection of data for a given application

Use of an ensemble of GCMs is the current best practice for accounting for the range and uncertainty of climate projections. Simulations from more than 60 GCMs, each run for multiple RCPs, were included in the IPCC's Coupled Model Intercomparison Project Phase 5 (CMIP5). However, use of an ensemble of 60 GCMs is intractable for most analyses at subglobal extents. Use of about 10 GCMs generally is sufficient to characterize the distribution of possible climate variation and change in future decades (Pierce et al 2009, McSweeney et al. 2012).

Each GCM reflects different assumptions, approximations, and algorithms, and therefore the accuracy with which different climate variables are simulated varies among GCMs. One cannot assume a relation between the accuracy with which a given GCM simulates historical climate and the GCM's response to changes in atmospheric concentrations of carbon dioxide (i.e., its climate sensitivity) (Stocker et al. 2013) Moreover, the accuracy of a given GCM's simulation of historical climate may not be related to the accuracy of its simulations of future climate (e.g., Pierce et al. 2009). Nevertheless, there is little basis for gauging the reliability of a GCM other than by its ability to simulate observed climate.

For example, the Climate Change Technical Advisory Group (CCTAG) of the California Department of Water Resources created a three-step, transferable process that evaluated GCM simulations of historical-climate metrics to select a subset of GCMs for relatively fine-resolution applications in the western United States (CCTAG 2015). In the first step, the CCTAG evaluated the accuracy with which each of 31 GCMs (those that were available at the beginning of their work) simulated historical climate at the global extent. Accuracy was assessed in part on the basis of the error between observed and projected seasonal cycles of radiative measures, winds, precipitation, and temperature (Gleckler 2008). Another screening criterion was the relations among GCMs. Because GCMs largely are numerical representations of the same physical processes, they are similar to some extent (Knutti et al. 2013, Swanson 2013). Models that are developed by a given climate center or modeling group (e.g., the Hadley Centre) usually are more similar than models developed by different climate centers. The CCTAG did not retain more than two GCMs from the same modeling center. The CCTAG also retained some models that were relatively accurate at regional and local extents, but might be less accurate at the global extent. This step reduced the set of retained GCMS from 31 to 19.

In the second step, the CCTAG evaluated the accuracy with which each retained GCM simulated historical climate at the extent of the western United States, including mean seasonal spatial patterns, the amplitude of seasonal cycle, the diurnal temperature range, annual to decadal variance in climate variables, and relations between precipitation in the western United States and the El Niño Southern Oscillation (ENSO) (Rupp et al. 2013). This step reduced the set of retained GCMs from 19 to 15.

In the third step, the CCTAG evaluated the accuracy of each of the 15 GCMs relative to specific applications. Metrics relevant to water management in California, for example, included the maximum three-day precipitation total and the number of dry years per decade.

Additionally, one can assess the ability of GCMs to simulate weather and climate features for the correct physical reasons during the historical period, which is necessary to accurately simulate such features in projections of future climate. For example, Gershunov and Guirguis (2012) assessed the ability of several GCMs to simulate California heat waves in response to realistic patterns of atmospheric pressure, and then used the most accurate model to study projected heat waves.

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