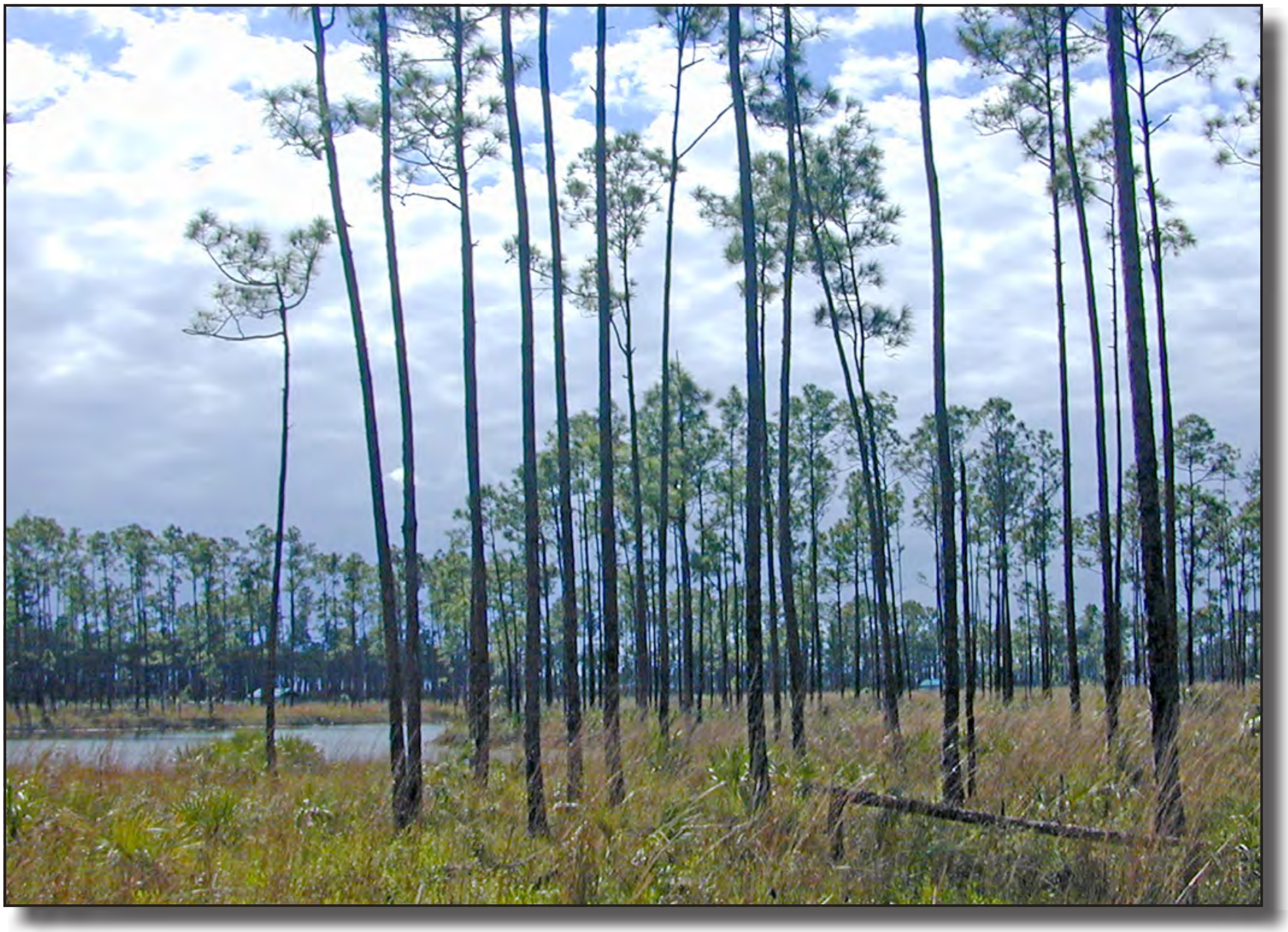
# Downscaled Climate Projections for the Southeast United States: Evaluation and Use for Ecological Applications



Open-File Report 2014–1190

U.S. Department of the Interior
U.S. Geological Survey

**Cover.** Long Pine Key in Everglades National Park, Florida (Photograph by Heather Henkel, U.S. Geological Survey).

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Suggested citation:
Wootten, Adrienne, Smith, Kara, Boyles, Ryan, Terando, Adam, Stefanova, Lydia, Misra, Vasu, Smith, Tom, Blodgett, David, and Semazzi, Fredrick, 2014, Downscaled climate projections for the Southeast United States—Evaluation and use for ecological applications: U.S. Geological Survey Open-File Report 2014–1190, 54 p., *http://dx.doi.org/10.3133/ofr20141190.*

ISSN 2331-1258 (online)

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# Downscaled Climate Projections for the Southeast United States: Evaluation and Use for Ecological Applications

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## 1 Introduction

Climate change is likely to have many effects on natural ecosystems in the Southeast U.S. The National Climate Assessment Southeast Technical Report (SETR) indicates that natural ecosystems in the Southeast are likely to be affected by warming temperatures, ocean acidification, sea-level rise, and changes in rainfall and evapotranspiration (Ingram and others, 2013). To better assess how these climate changes could affect multiple sectors, including ecosystems, climatologists have created several downscaled climate projections (or downscaled datasets) that contain information from the global climate models (GCMs) translated to regional or local scales. The process of creating these downscaled datasets, known as downscaling, can be carried out using a broad range of statistical or numerical modeling techniques. The rapid proliferation of techniques that can be used for downscaling and the number of downscaled datasets produced in recent years present many challenges for scientists and decisionmakers in assessing the impact or vulnerability of a given species or ecosystem to climate change. Given the number of available downscaled datasets, how do these model outputs compare to each other? Which variables are available, and are certain downscaled datasets more appropriate for assessing vulnerability of a particular species? Given the desire to use these datasets for impact and vulnerability assessments and the lack of comparison between these datasets, the goal of this report is to synthesize the information available in these downscaled datasets and provide guidance to scientists and natural resource managers with specific interests in ecological modeling and conservation planning related to climate change in the Southeast U.S. This report enables the Southeast Climate Science Center (SECSC) to address an important strategic goal of providing scientific information and guidance that will enable resource managers and other participants in Landscape Conservation Cooperatives to make science-based climate change adaptation decisions.

[1] State Climate Office of North Carolina, North Carolina State University.

[2] Department of Marine, Earth, and Atmospheric Sciences, North Carolina State University.

[3] Department of the Interior Southeast Climate Science Center.

[4] Center for Ocean Atmosphere Prediction Studies, Florida State University.

[5] U.S. Geological Survey Southeast Ecological Science Center.

[6] U.S. Geological Survey Center for Integrated Data Analytics.

### 1.1 Motivation and Goals

Downscaling allows for the exploration of how regional climate change might be experienced in the context of local and regional areas. Although downscaling is potentially useful for ecological modeling and conservation planning/management decisions, there is no current literature that evaluates available downscaled datasets with regard to these same applications. In addition, there is no current literature that offers a comparison of the structure of these downscaled datasets with regard to the needs of ecologists in the Southeast U.S. The goals of this report are twofold. First, this report will synthesize available literature and information about six downscaled datasets that cover the Southeast U.S. Second, this report will use the synthesis of available literature and the evaluation of downscaled datasets to make recommendations regarding the use of downscaled climate data and future work needed to make these datasets more useful for ecological modeling and decisionmaking. The remainder of this chapter focuses on a discussion of the aspects of global and regional climate and climate modeling. Chapter 2 focuses on the different kinds of downscaling techniques. Chapter 3 focuses on the differences between six downscaled datasets and the information needed for ecosystem modeling in the Southeast U.S. Chapter 4 presents the results of an initial evaluation of the six downscaled datasets. Finally, Chapter 5 presents the conclusions and recommendations from this report.

### 1.2 Aspects of Global and Regional Climate

**Climate** is defined as the average weather in a particular location. Climate includes the descriptions of the mean, variability, and other high order statistics of relevant variables, such as temperature, precipitation, and wind. The **climate system** is an interactive system with five main components: the atmosphere, hydrosphere (oceans), cryosphere (ice sheets, snow fields, glaciers, sea ice, and permafrost), land surface (vegetation and soils), and the biosphere (marine and terrestrial biota). The world's oceans are the main drivers of the climate system, while the general circulation of the atmosphere is the mechanism by which most of the energy received from the sun or stored in the oceans is redistributed around the planet. Atmospheric motions carry heat from the tropics to polar regionsas well as water vapor from oceans into inland areas. This general circulation is formed by the uneven heating of the Earth's spherical, tilted, and rotating surface area by the sun and helps maintain the balance of energy in the global climate as it responds to temperature and humidity gradients by transporting energy and moisture in the atmosphere (Hartmann, 1994).

The climate of a terrestrial area depends on its latitude, altitude, prevailing wind direction, and nearby water bodies or mountains in addition to the general circulation of the atmosphere. The climate of the Southeast is warm and wet compared to the rest of the continental United States (Karl and others, 2009) due to its location near the Gulf of Mexico and the Atlantic Ocean. Temperatures typically are warmer equatorward, with a steeper meridional temperature gradient in the winter than in the summer. The average annual temperature of the Southeast has not changed significantly over the entire past century as a whole, but there has been a 2 degrees Fahrenheit (°F) (1.1 degrees Celsius (°C)) increase in annual average temperature between 1970 and 2008 with the greatest increase in temperature occurring during the winter season (Karl and others, 2009). The number of days with freezing temperatures increases northward with the Florida Keys reaching freezing temperatures less than once per year and northern Virginia having freezing temperatures 150 days per year (Mac and others, 1998). The number of days with below-freezing temperatures has decreased by 4 to 7 days per year for most of the Southeast since the mid-1970s (Karl and others, 2009). More recently, and Misra and Michael (2013) have shown that the observed temperature trends in the Southeast are affected by land-cover and land-use changes (e.g., irrigation or urbanization). The National Climate Assessment contains further information regarding the climate of the Southeast U.S. (accessed August 13, 2014, at *http://www.globalchange.gov/ncadac*).

## 1.3 The Basics of Climate Modeling

### 1.3.1 Modeling Basics

A **global climate model (GCM)** is a numerical model that uses known physical laws and relations to simulate the general climate patterns of the planet. The underlying modeling principles of GCMs are similar to (and takes their roots from) models used in weather forecasting. Although GCMs can be broken down into several components (atmosphere, land, ocean), each component works by dividing the "model" of the earth into a grid of some resolution and solving a series of equations at each grid point and time. For all GCMs the basic framework of the atmospheric component involves solving the equations that describe the conservation of momentum, energy, and mass for a fluid (in addition to a water vapor conservation equation for air) and which are affected by the general circulation of the atmosphere (Hartmann, 1994). GCMs focus on time scales of seasons to centuries and currently have spatial scales of 100–300 kilometers (km) and many vertical layers to represent the atmosphere. Figure 1.1 shows a schematic of physical processes in the modeling environment. This schematic shows the grid that covers the globe in a GCM. The grid spacing and processes simulated in a GCM allow the model to simulate the general circulation of the atmosphere and ocean (Hartmann, 1994); however, multiple physical processes occur between the grid points of a GCM (e.g., clouds, precipitation, sea ice processes, thunderstorms, etc.). These processes are represented using parameterizations. **Parameterization** is a statistical representation of the effects of the sub-grid scale processes on the grid scale (or resolved processes) of the GCM. Thus, parameterizations are used so that important physical processes that cannot be directly simulated through numerical computation can still be incorporated into the model. Among the processes that typically are parameterized in a GCM are precipitation, clouds, atmospheric and surface radiation, land surface processes, turbulent fluxes and exchanges at interfaces of land-ocean-air, and friction, which are difficult to simulate accurately at the GCM scale (Hartmann, 1994). Clouds and rainfall are an example of some of the processes that are parameterized because the processes that create clouds and rainfall occur at less than 1 km spatial resolution, and the GCM simulates processes at 100 km or more.

Due to advances in computing power, the number of processes included in GCMs continues to increase (Figure 1.2). Until the early 1990s, climate models incorporated primarily atmosphere and land surface processes. More recent climate models, however, incorporate atmosphere, land surface, and ocean processes. In addition, these models have begun to include more complex representations of atmospheric aerosols, the carbon cycle, and dynamic vegetation. Dynamic vegetation allows the vegetation to change in the modeling environment as the rest of the modeled climate changes, which is an improvement over older climate models where the vegetation is held constant to a specific reference period.

### 1.3.2 Emissions Scenarios

To project future changes to the climate, scenarios must be developed that prescribe possible forced changes to the earth's energy balance, and thus its climate. These "forcings" could originate from natural (e.g., volcanic eruptions or changes in the sun's energy output) or manmade (e.g., combustion of fossil fuels) sources. **Emissions scenarios** are "what-if" scenarios that specify future trajectories of important greenhouse gasses such as carbon dioxide. The scenarios may

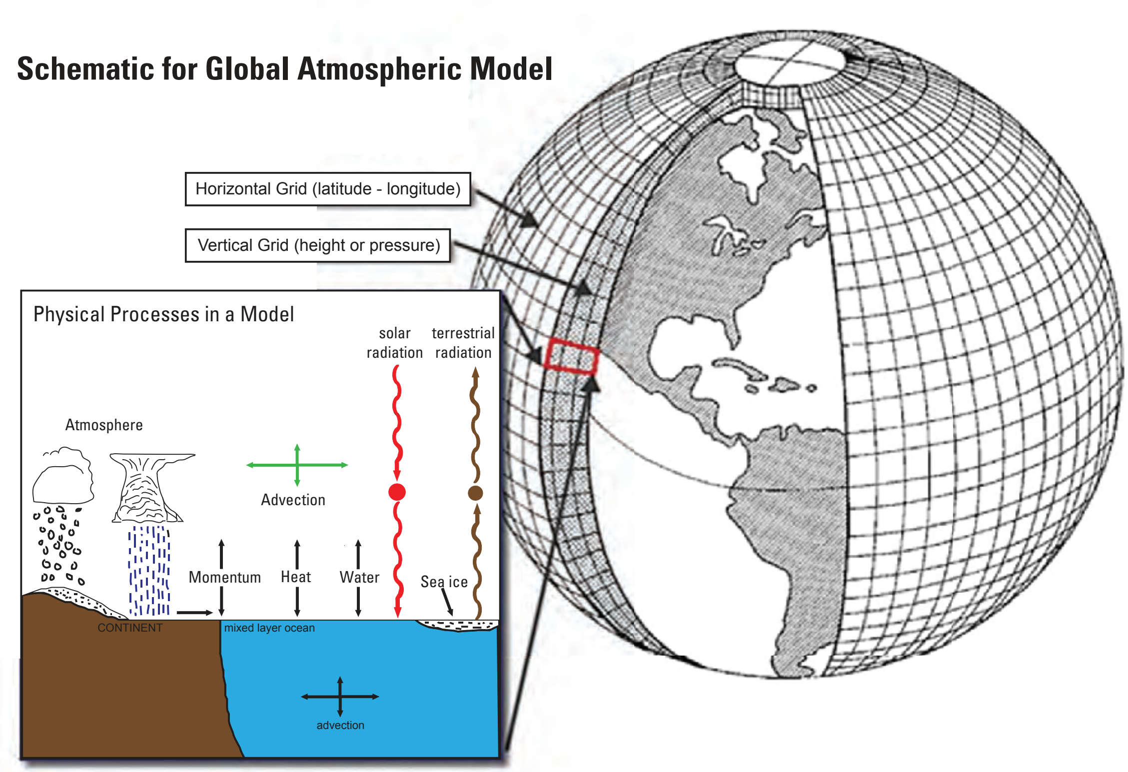


**Figure 1.1.** Schematic of the global atmospheric portion of a Global Climate Model. Original image retrieved from NOAA (*http://docs.lib.noaa.gov/noaa_documents/time_capsules/2007/disc_7/celebrating200years.noaa.gov/breakthroughs/climate_model/welcome.html*).

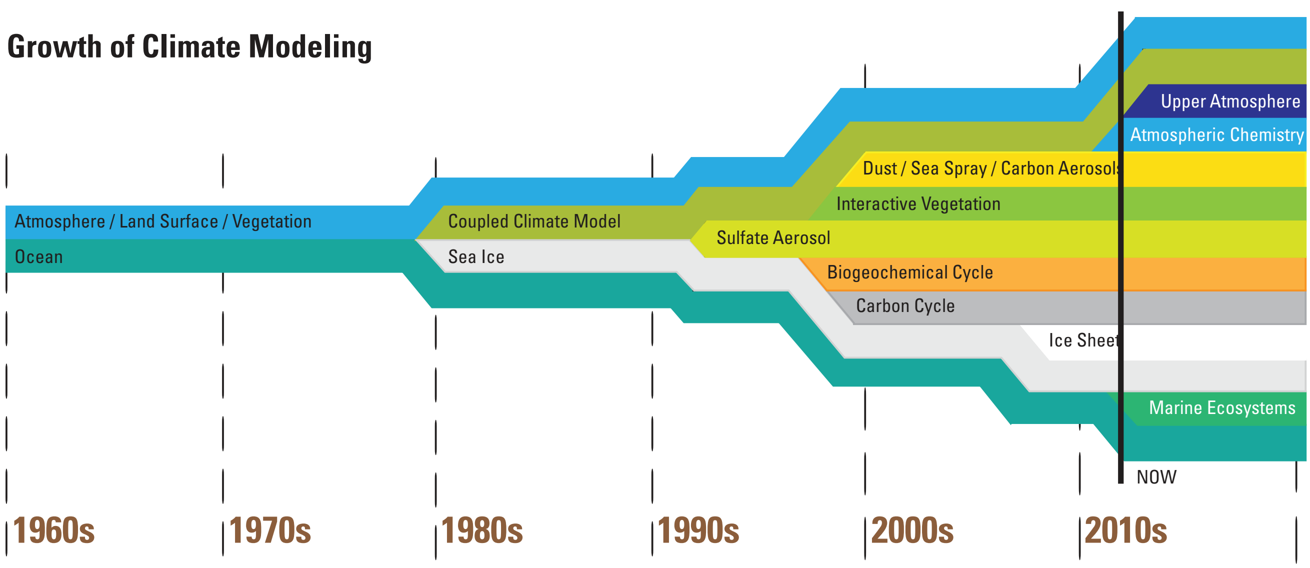


**Figure 1.2.** Progression of climate models—Process inclusion since the 1960s. Original image from Intergovernmental Panel on Climate Change 2001, retrieved from University Corporation for Atmospheric Research.

also include the amount and type of land-use and land-cover changes that could take place in the future. In the past, emission scenarios developed by the Intergovernmental Panel on Climate Change (IPCC) for the periodic Assessment Reports (AR) have been based on assumptions on economic and population growth as well as technology development and other factors (IPCC, 2009). But it is important to recognize that no scenario is assumed to be more likely than any other. The downscaled projections evaluated in this report are based on a set of IPCC scenarios developed for the third and fourth assessment reports. The scenarios, listed from highest to lowest emissions are A1FI, A1B, A2, and B1. The A1FI scenario depicts the highest amounts of carbon emissions with energy use coming from the burning of fossil fuels. This is also the scenario that has most closely approached recent observed emissions. The A1B is similar to the A1FI scenario except that not all energy comes from the burning of fossil fuels. The A2 scenario is considered to be "business as usual" where population growth and emissions keep increasing at the current rate. The B1 scenario assumes new efficient technologies are spread quickly and are massively used so that less greenhouse gasses are emitted. Emissions scenarios are used as one way to account for uncertainty about future human activities. The scenarios listed above are part of the Special Report on Emissions Scenarios (SRES) produced by the IPCC for use in GCMs for the IPCC Fourth Assessment Report. For the Fifth Assessment Report, the IPCC has produced new Representative Concentration Pathways (RCPs) as inputs for climate modeling. The SRES scenarios and RCPs were constructed differently from each other. The SRES scenarios were constructed by making different assumptions for future greenhouse gas pollution, land use, and other driving forces. In contrast, the RCPs focus on different pathways of radiative forcing, with the conceptualization that there are multiple socioeconomic and technological development scenarios that can lead to the same amount of radiative forcing applied to the climate (*http://www.wmo.int/pages/themes/climate/emission_scenarios.php*). It is important, however, to note that the resulting emissions and radiative forcing from the SRES scenarios and RCPs are similar through the middle of the century. In addition, the similarities between the SRES scenarios and RCPs lead to similar results from the GCMs used in the Fourth and Fifth IPCC Assessment Reports (Knutti and Sedláček, 2012). Therefore, although this report focuses on SRES, the analyses, results, and recommendations of this report should still be applicable to the RCPs in the Fifth Assessment Report. Before continuing to discuss downscaling, it is also important to discuss the different sources of uncertainty in climate modelling.

### 1.3.3 Uncertainty in Climate Modeling

One of the most important aspects of climate modeling and downscaling is the uncertainty that arises between the output from the model and what will actually be observed in the future. Several different kinds of uncertainty are represented in climate modeling and downscaling. These types of uncertainty include:

- Natural uncertainty
- Scientific uncertainty
- Scenario uncertainty

**Natural uncertainty** is related to the natural climatic fluctuations that arise in absence of human influence. For example, the El Niño Southern Oscillation and the North Atlantic Oscillation change from year to year (or on multiyear time scales of less than a decade) and both have an impact on the temperatures and precipitation in the Southeast. Some of these natural fluctuations are external to the climate system, such as solar variability. Other natural fluctuations, such as volcanic activity, are internal to the climate system. **Scientific uncertainty**, also known as model, response, or structural uncertainty, is related to how well the physical processes of climate are understood and to how those processes are represented in individual models. For instance, although we know the climate system is sensitive to emissions, there is still a question of exactly how sensitive the climate system is to emissions. In addition, the ability to simulate the climate system is still limited, particularly at local and regional scales. Although there are many physical processes included now in a GCM, our understanding of how these processes affect the climate system is still incomplete. Given this, how these processes are represented in GCMs may vary, and in turn the simulated response to the same amount of radiative forcing may be different. For reference, **radiative forcing** is defined as "a change in the balance between incoming solar radiation and outgoing infrared (i.e., thermal) radiation" (U.S. Environmental Protection Agency, 2013). **Scenario uncertainty**, also known as human uncertainty, is a source of uncertainty related to human activities, particularly what future emissions may be from human activities. All three of these sources of uncertainty are present in all climate projections; however, the peak in each of these sources of uncertainty happens at different times in a projection for different variables. Hawkins and Sutton (2009) point out that for the first decade of a projection, natural uncertainty is the largest source of uncertainty for temperature. Hawkins and Sutton (2009) and Hayhoe (2012) also point out that scientific uncertainty is largest for the third decade into the projection, and human uncertainty is largest for the ninth decade into the projection for temperature. In the case of precipitation, Hawkins and Sutton (2011) show that natural uncertainty is the largest source for the first decade. However, Hawkins and Sutton (2011) and Hayhoe (2012) also show that scientific uncertainty is the largest source of uncertainty for both the third and ninth decades of a projection for precipitation. This comparison points out that the major sources of uncertainty for different time periods in the larger scale projections can be different for different variables of interest. Multiple GCMs and emissions scenarios are used in each dataset in order to capture these different forms of uncertainty. From this, it is possible to quantify the uncertainty by comparing a variable from multiple GCMs.

Although the projections from GCMs reflect the three main sources of uncertainty, an additional source of uncertainty is referred to by Hayhoe (2012) as **scale uncertainty**. Changes on a global scale affect locations in different regions in different ways because the characteristics of each region are different. Downscaling, aside from what is previously described, is also used to address uncertainty that is related to the dynamics of a region of interest.

# 2 Downscaling

Most GCMs successfully capture large-scale atmospheric patterns and global and continental temperature responses to changes in greenhouse gas emissions. In that sense the models can be used to better understand how human actions (i.e., greenhouse gas emissions) can alter the Earth's climate. Computational constraints limit the scale at which GCMs operate, which is usually too coarse to aid decisionmakers that are concerned with local or regional adaptations to climate change. Downscaling is used to address this limitation by translating the coarse-scale GCM output to the regional or local scale. However, it is important to note that downscaling does not resolve scientific uncertainty or some finescale processes (such as clouds).

The common definition of **downscaling** is described by Benestad and Chen (2008) as "the process of making the link between the state of some variable representing the large space and the state of some variable representing a much smaller space." While numerous techniques have been used that could fall under this definition, all can be broken down into two basic groups. The first of these groups is dynamic or numerical downscaling, and the second group is empirical statistical downscaling (ESD; also referred to as statistical downscaling or empirical downscaling).

## 2.1 Dynamic Downscaling

**Dynamic downscaling,** also known as numerical downscaling, employs methods similar to those discussed previously for GCMs. This process usually refers to the use of limited area models (LAMs; e.g., Giorgi, 1990; Frogner and others, 2006; Tudor and Termonia, 2010). LAMs are high resolution models for a limited area that are one-way nested at their lateral boundaries with a GCM. That is, the GCM provides input for the boundaries of the LAM, but the LAM does not return any information to the GCM. LAMs that are used for climate-scale time periods (i.e., a season or longer) are commonly referred to as regional climate models (RCMs; Wang and others, 2004; Laprise, 2008). Because these models cover only a portion of the Earth, they require input at the area boundaries from a GCM for variables such as surface pressure, wind circulation, air temperature and humidity, and sea-surface temperature. The spatial resolution of RCMs and LAMs is on the order of tens of kilometers, but can be as fine as a few kilometers if grids are nested into a coarser RCM simulation. Dynamic downscaling techniques simulate most physics in the climate system (similar to weather models and GCMs) and are capable of producing simulations that are physically consistent throughout the region being modeled. There are also several drawbacks associated with dynamic downscaling techniques.

- **Computationally expensive—**Given the calculations involved over the desired region (that is, the region to be modeled), a tremendous amount of computing resources and time are required for computation. This can limit the number of GCMs and emissions scenarios that are considered for climate change applications. It can take months using a supercomputer to run one RCM over an area the size of the Southeast U.S. to downscale climate projection that covers a couple of decades.

- **Systematic errors—**Errors in the dataset are introduced by inaccuracy in the models, such as how precipitation and other metrics are parameterized. RCMs and LAMs inherit the systematic errors of the GCM that is being downscaled in addition to having their own systematic errors. In most cases, such errors can be accounted for with bias correction of the RCM or LAM output so that the dataset has the same statistical properties as observations over the same time and area.

- **Parameterization schemes—**Approximations of processes that occur at a finer resolution than the model represents are created on the basis of present climate and, therefore, may not be valid in future climates (Benestad and others, 2008).

### 2.1.2 Statistical Downscaling

**Statistical downscaling**, or more formally, empirical statistical downscaling (ESD), refers to a group of downscaling techniques that use statistical methods and observed climate data to build the relation between regional/local and global scales. Many techniques can be defined as statistical downscaling techniques, but the techniques themselves generally fall into one of three categories:

- **Transfer functions or regression methods** typically are the simplest ESD techniques used to determine the relation between large area and site-specific surface climate data or large-scale upper air data and local surface climate data. These techniques include linear and multiple linear regression, canonical correlation analysis, principal components analysis (or empirical orthogonal functions), artificial neural networks, and kriging (Barrow, 2002; Wilby and others, 2004; e.g., Heyen and others, 1996; Busuioc and others, 2001 and

2006; Widmann and others, 2003; Benestad, 2007; Ghosh and Mujumdar, 2008; Hoar and Nychka, 2008). Statistical downscaling approaches typically are less computationally demanding than dynamic downscaling approaches and, as a result, can downscale a large number of GCMs relatively easily. However, these approaches require a large amount of observation data to establish statistical relations that may only be valid within the historical period used for calibration (Barrow, 2002).

- **Weather typing techniques** function similarly to transfer functions; however, weather typing focuses on determining the relation between atmospheric circulation types and local weather patterns. These circulation types or weather classes can be determined objectively through cluster analysis (e.g., Corte-Real and others, 1999; Huth, 2000; Kidson, 2000; Hewitson and Crane, 2002 and 2006) or subjectively through various published schemes (e.g., Bardossy and Caspary, 1990; Jones and others, 1993). Weather type techniques include analog methods, self-organizing maps, and Monte Carlo techniques (Wilby and others, 2004; e.g., Hughes and others, 1993; Conway and Jones, 1998; Zorita and Von Storch, 1999; Timbal and McAvaney, 2001). Although these types of techniques are founded on links between large-scale climate and local weather conditions, the scenarios that are produced are relatively insensitive to future climate forcing (that is, using only large-scale circulation may not account for all projected local changes; Barrow, 2002).

- **Weather generator techniques** replicate the statistical attributes of a local climate, but do not replicate the observed sequences of events (Wilks and Wilby, 1999; Wilby and others, 2004). Most commonly, these generators make use of Markov chains (e.g., Richardson and Wright, 1984; Baigorria and Jones, 2010) or the probability of dry and wet spells of various lengths (e.g., Racsko and others, 1991). Unlike the other statistical techniques, the parameters of a weather generator can be altered in accordance with scenarios of future climate change for both the mean and variability. Weather generators, however, are typically designed for use at independent, individual locations (Barrow, 2003).

Regardless of the category of statistical downscaling technique, several advantages and attractive features are shared by all statistical techniques (Von Storch and others, 2000; Varis and others, 2004).

- Statistical downscaling techniques are less computationally expensive than dynamic downscaling techniques, potentially allowing for analysis of many more model runs compared to dynamic downscaling.

- They are based on standard and accepted statistical procedures.

- Statistical techniques may be flexibly crafted for specific purposes.

- ESD techniques are able to incorporate historical climate information for the desired region.

There are also several disadvantages to using statistical techniques for downscaling (Goodess and others, 2001; Varis and others, 2004).

- Statistical downscaling techniques assume that the statistical relations will be unchanged in a future climate. This is related to issues of stationarity in statistical modeling. **Stationarity** implies that the statistical properties of a variable will be the same in time. It is not necessarily true that each variable will have similar statistical properties through time. The assumption of stationarity also implies that the error of the statistical process will be the same during current and future history.

- They require a long (> 20 years) and reliable data series to allow the statistical relations to be robust. Therefore, a number of meteorological and oceanic variables (which are likely relevant to terrestrial and aquatic ecology) cannot be statistically downscaled simply because the corresponding observations of these variables are either not available or not observed for a long enough period of time.

- Like dynamic downscaling techniques, statistical techniques are also affected by the errors used in GCM.

Given the numerous variety of techniques and their associated advantages and disadvantages, the question remains, *Why use downscaled datasets over the original GCM output datasets?* Many of the processes that have the strongest influence on ecosystems especially in the Southeast occur at resolutions finer than those of GCMs. This means that because the processes are parameterized in GCMs, they cannot provide an indication of local and regional scale patterns. For example, a GCM cannot provide detailed information regarding changes in precipitation over a state park compared to surrounding areas, but it can provide information regarding the change in average total precipitation for a season in a regional domain of interest. This is because a GCM is designed to capture larger scale patterns such as the location and strength of the jet stream. As such, a GCM is appropriate use for projections of larger scale patterns. However, the fact that a GCM must parameterize processes that occur at grid scales finer than the GCM resolution (e.g., rainfall and clouds) means that it is not appropriate to use GCM data for local guidance as in the state park example. In a coarse GCM, local areas known to receive more precipitation get spatially averaged with areas known to receive less precipitation—all of this is averaged together into a single point in the GCM. Downscaling incorporates information regarding local variations in climate that are not represented in the GCMs. This process allows downscaling to better represent the influence of processes such as clouds and precipitation and as a result gives more confidence regarding local changes than a GCM can provide.

## 2.3 Bias Correction

In addition to the downscaling techniques themselves, an additional important component known as bias correction is applied in a downscaling process. **Bias correction** is a process that removes or reduces the biases that occur in GCM and RCMs and are inherited by the downscaled data. The first kind of bias removed is **systematic bias**. This type of bias is when the mean of the GCM data or downscaled data differs somewhat consistently from the observed mean for a given variable. For example, given the average temperature over a historical 30-year period projected by the GCM may be 2–3 °C warmer or colder than the observed average temperature for the same period over a region. A second kind of bias is associated with the internal variability of a model (Palmer and Weisheimer, 2011). This bias is associated with the lack of representation of processes that occur at grid scales finer than the resolution of the GCM. This can lead to an over or underrepresentation of how a variable of interest (temperature, precipitation) varies from year to year. For instance, an underrepresentation of the variability of precipitation can lead to fewer wet periods and fewer dry periods, while an overrepresentation may produce too many wet or dry periods.

Bias is determined for GCMs and downscaled data using hindcast simulations. A **hindcast simulation** is when a GCM is run for a historical period. The resulting GCM and downscaled data for a variable are compared to the observed data for the same variable for this historical period, which allows for the assessment of model biases.

Bias is removed from climate model data in multiple ways. One of the most simple ways of removing bias is to add the difference between the projection and a hindcast simulation to the observed climatology of an area. The change in temperature, computed as the difference between the projected value and the hindcast simulation, is added to the observed climatology to determine a bias corrected projection. It is also common to use the anomalies (or departures) from a reference period to investigate how a variable will change over a given time period. Differences from the mean are commonly used for temperature change, while ratios are more commonly used for precipitation change (IPCC-TGCIA, 1999). This reference period should be a time period that

- Is representative of the recent average climate in the study region
- Encompasses a range of climate variations, which ideally, include historically warm and cool (wet and dry) periods
- Covers a time period where data are available
- Is consistent, or able to be compared, with reference periods used in other impact assessments.

The reference period used most often by climatologists is 1961–1990. This period was defined by the World Meteorological Organization and has been used in previous IPCC Assessment Reports. However, a 30-year time period may not be long enough to account for natural climatic variability on a multidecadal timescale, which could influence long-term impacts (IPCC-TGCIA, 1999).

Another way to remove bias is a simple normalization technique. For this technique, the mean and standard deviation of the model of the current climate are replaced with the mean and standard deviation of observed historical data. The biases from the current climate are assumed to be the same for the model of the future climate by this technique. There are also bias correction techniques that use quantile based mapping. Watanabe and others (2012) compared several bias correction techniques for both temperature and precipitation. They found negligible differences between the bias-corrected data and observations for historical data; however, there were large differences in future simulations that were based on the bias correction method used.

# 3 Downscaled Datasets and Ecosystems in the Southeast

Numerous downscaled datasets (both statistical and dynamic) are now available. This section includes basic information for six available datasets (e.g., who created it, where the dataset can be found, associated publications) and an analysis of metadata. These datasets are all accessible online, but there are important basic differences in the metadata for each product. **Metadata** in this case refers to the characteristics of each dataset. For reference, what we have defined as metadata information in this synthesis includes:

- Type of downscaling technique used
- GCMs and emissions scenarios used
- Spatial resolution and domain covered
- Temporal resolution and time period
- Available output variables (temperature, precipitation, etc.).

Our survey is not exhaustive, but includes the most widely used, peer reviewed, and publicly available downscaled datasets. These six downscaled datasets also represent a range of downscaling techniques used to create them. Half of these datasets were created using statistical downscaling techniques, while the remaining three datasets were created using dynamic downscaling approaches.

1. **CLAREnCE10 (COAPS Land-Atmospheric Regional Ensemble Climate Change Experiment)—**The Center for Ocean Atmospheric Prediction Studies (COAPS) at Florida State University – Accessible at *http://elnino.coaps.fsu.edu/thredds/catalog.html* (Lydia Stefanova, written commun., 2013; Misra and others, 2011; Stefanova, Misra, Chan, and others, 2012; Stefanova, Misra, and Smith, 2012)

2. **SERAP (Southeast Regional Assessment Project)—**Texas Technical University – Accessible through the U.S. Geological Survey (USGS) Center for

Integrated Data Analytics (CIDA) GeoData Portal *http://cida.usgs.gov/gdp/* (Dalton and Jones, 2010; Stoner and others, 2012)

3. **BCSD (Bias Corrected Spatial Disaggregation)—**Santa Clara University/U.S. Department of Energy – Accessible through the USGS CIDA GeoData Portal *http://cida.usgs.gov/gdp/* (Maurer and others, 2007)

4. **Hostetler Datasets—**U.S. Geological Survey/Oregon State University – Accessible through the USGS CIDA GeoData Portal *http://cida.usgs.gov/gdp/* (Hostetler and others, 2011)

5. **NARCCAP (North American Regional Climate Change Assessment Program)—**National Center for Atmospheric Research (NCAR), National Oceanic and Atmospheric Administration (NOAA), National Science Foundation (NSF), U.S. Environmental Protection Agency (EPA), Department of Energy (DOE) – Accessible at *http://www.narccap.ucar.edu/* (Mearns and others, 2009)

6. **CCR (Center for Climatic Research)—**The Center for Climatic Research, Wisconsin Initiative for Climate Change Impacts (WICCI) – Accessible through the Center for Climatic Research and the USGS CIDA GeoData Portal *http://cida.usgs.gov/gdp/* (Lorenz, 2014)

In this section we will detail the differences between these downscaled datasets with regard to what we have defined as the metadata for each dataset. Throughout this section we will refer often to Table 3.1, which compares the metadata for each of these datasets, and accompany this discussion with other figures to clarify the differences between these datasets. The first set of differences we consider are the downscaling techniques, GCMs, and emissions scenarios used to create these datasets.

## 3.1 Downscaling Techniques, GCMs, and Emission Scenarios

Considering the differences presented in Tables 3.1 and 3.2, it is apparent that the computational expense of dynamic downscaling limits the number of GCMs and emissions scenarios that can be considered in the creation of a dataset. However, because dynamic downscaling considers the full physics of the atmosphere and ocean, there are many more climate variables available or derivable from these datasets. In contrast, the statistical techniques are much less computationally expensive than dynamic techniques. As such, statistical techniques are able to consider many more GCMs and emissions scenarios that are available, but the number of available variables for these datasets is limited to those for which a robust model can be derived.

The limitation in the number of variables statistically downscaled is related to the use of observational data in building statistical relations between global and regional/local scales. Although each GCM used has multiple variables available, not all the same variables have long observational records across the United States. For example, observational records of temperature in the U.S. can be longer than 100 years. However, in some regions there are less than 20 years of observations of solar radiation, which is a key component for estimating evapotranspiration. As such, the resulting number of variables that can be statistically downscaled are limited to those with long observation records. As mentioned previously, stationarity implies that a variable will have similar statistical properties through time. For example, a non-stationary variable may have a period where the standard deviation or mean is very different from another period. As such, incorporating a long observational record allows statistical downscaling techniques to account for issues with stationarity during the historical periods. Using a period of 10 years to build the statistical relations involved risks chosing one period that may have a different mean or standard deviation compared to another period. Therefore, long observational records are important to account for stationarity during this historical record. CCR, BCSD, and SERAP datasets are limited to temperature and precipitation at either daily or monthly time scales.

While each of these datasets is classified as being created with either statistical or dynamic downscaling techniques, as mentioned previously there are several kinds of statistical and dynamic downscaling techniques, and the technique used to create each downscaled dataset may have impacts on the utility of the guidance produced. For example, SERAP uses a modified statistical asynchronous regression between each GCM used and the local scale. The Bias Corrected Spatial Disaggregation technique is used to create the BCSD dataset. For the CCR dataset, a combination of linear and logistic regression with a potential model are applied to downscale temperatures and precipitation (Lorenz, 2014). All of these techniques fall into a category of statistical downscaling techniques known as transfer functions (Varis and others, 2004). These types of statistical techniques are among the most simple of techniques and can produce an ensemble of high resolution climate scenarios very easily. However, as noted previously, the techniques in this category tend to have poor representation of extreme events. For instance, Maurer and Hidalgo (2008) note that BCSD tends to have more error in the extremes of the temperature and precipitation distributions compared to other downscaling techniques.

Just as different techniques and methods are used to derive the statistically downscaled model output, the NARCCAP, Hostetler, and CLAREnCE10 datasets are created using different variations of dynamic downscaling. These variations are mostly in terms of the RCMs used to downscale the GCM output (each with different parameterization schemes). In addition, NARCCAP, Hostetler, and CLAREnCE10 also downscale different GCMs. Similar to GCMs, individual RCMs have uncertainties from their parameterization schemes and spatial and temporal discretization. RCMs also inherit the uncertainty from the GCM that is being downscaled.

**Table 3.1.** Metadata comparison between the six downscaled datasets.

| Dataset (reference) | Spatial resolution | Spatial domain | Temporal resolution | Time period(s) | Type of technique | Gcms used | Emissions scenarios used | Available output variables |
|---|---|---|---|---|---|---|---|---|
| CLAREnCE10 (Stefanova, written communication) | 10 km | Southeast U.S. | hourly | 1968–2000, 2038–2070 | dynamic | CCSM3, HADCM3, GFDL 2.1 | A2 | precipitation, specific humidity, wind speed, wind direction, temperatures, surface heat fluxes, pressure, roughness, snowfall rate water equivalent |
| Hostetler (Hostetler and others, 2011) | 50, 15 km | Western North America and Eastern North America | 3 hourly and 6 hourly | 1968–2099 | dynamic | GFDL 2.0, ECHAM5, GENMOM | A2 | air, ground and foliage temperatures, temperature thresholds, growing degree days (base 10 and 5C), cooling degree days (base 22C), heating degree days (base 15.5C), radiation, sensible heat flux, ET, precipitation, snow water equivalent, specific and relative humidity, soil moisture, runoff, wind speed and direction, more |
| NARCCAP (Mearns and others, 2009) | 50 km | North America | 3 hourly and daily | 1971–2000, 2041–2070 | dynamic | CCSM, CGCM3, GFDL 2.1, HADCM3 | A2 | temperatures and precipitation (online), more available offline to registered users |
| CCR (Lorenz, 2014) | 0.1 degree ~ 11 km | Eastern U.S. and Southern Canada | daily | 1961–2000, 2046–2065, 2081–2100 | statistical | CGCM3, CNRM, CSIRO 3 / 3.5, GFDL 2.0, GISS AOM, GISS MODEL E, IAP, MIROC, ECHO, ECHAM5, CGCM2 | B1, A1B, A2 | max and min temperatures, precipitation |
| BCSD (Maurer and others, 2007) | 1/8 degree ~ 12 km | Continental U.S. | monthly | 1950–2099 | statistical | BCM2, CGCM3, CNRM, CSIRO, GFDL 2.0, GFDL 2.1, GISS 2, INMCM3, IPSL CM 4, MIROC 3.2, ECHO, ECHAM5, CGCM 2.3, CCSM 3,PCM 1.2, PCM 1.3, PCM 1.4 , HADCM 3 | A1B, A2, B1 | average temperature, precipitation |
| **SERAP (Stoner and others, 2012)** | 12 km | Continental U.S. | daily | 1960-2099 | statistical | PCM, CCSM3, GFDL 2.0 / 2.1, HADCM3, GCM2, CGCM3, CNRM, ECHAM5, ECHO | A1FI, A2, A1B, B1 | max and min temperatures, precipitation |

For information on the individual global climate models (GCMs) included in these downscaled datasets, see Randall and others (2007).

**Table 3.2.** Number of GCMs and emissions scenarios considered by each downscaled dataset.

| Downscaled dataset | Number of GCMs downscaled | Number of emissions scenarios used |
|---|---|---|
| CLAREnCE10 | 3 | 1 |
| Hostetler | 3 | 1 |
| NARCCAP | 4 | 1 |
| CCR | 10 | 3 |
| BCSD | 18 | 3 |
| SERAP | 12 | 4 |

NARCCAP contains data from six different RCMs that have been used to downscale four GCMs. Each RCM has a different combination of parameterizations for land surface, vegetation types, clouds, and aerosols. The GCMs used also each have a different combination of parameterizations. There are not data yet for every combination of RCMs and GCMs in NARCCAP. The Hostetler dataset is created using only one RCM (RegCM3) to downscale three GCMs (different from the GCMs used in NARCCAP) with differing parameterizations. CLAREnCE10 uses the Florida Climate Institute/Florida State University Regional Spectral Model (RSM) RCM to downscale three of the GCMs used in NARCCAP. Although the RSM is closely related to the Experimental Climate Prediction Center model used in NARCCAP, RSM has different parameterizations than the RCMs used in the NARCCAP dataset. The parameterizations are important because each parameterization is created slightly differently from other parameterizations created for representing the same process. For example, different parameterizations represent convection slightly differently and this in turn effects the results produced by a given GCM or RCM.

## 3.2 Spatial Domain and Resolution

In this section, we will further explore the spatial domain and resolution differences between these datasets. Most of the downscaled datasets have archived model output for the continental U.S. or for most of North America (Table 3.1). NARCCAP and Hostetler cover North America, while CLAREnCE10 only covers the Southeast U.S. The SERAP and BCSD datasets cover the continental U.S. while the CCR dataset focuses on the Eastern U.S. However, although Table 3.1 gives a sense of the domain covered, the domain actually represented by each downscaled dataset will be different given different map projections, offshore coverage, and multiple domains covering a larger area. For example, consider Figure 3.1, which shows the modeling domain of NARCCAP. Areas with a lack of color reflect regions where NARCCAP has no data and the domain covered by this downscaled dataset takes its shape because of the map projection used. Figure 3.2 shows the five separate modeling domains used by the Hostetler datasets. The Southeast U.S. is contained in the ENA or Eastern North America Domain, while the Western U.S. is covered by the remaining four domains used.

An additional important difference is that some of these datasets do not provide information offshore. NARCCAP (as shown in Figure 3.4) does provide output offshore of the Southeast U.S. Figure 3.3 shows examples of the output from the (a) BCSD dataset, (b) CLAREnCE10, and (c) SERAP for which there is no output available over the open ocean and the (d) Hostetler dataset for which there is output available over open ocean. Finally, Figure 3.4 displays the domain of the CCR dataset, which extends into southern Canada, but also does not provide output over the ocean. While all of these downscaled datasets cover land masses in the Southeast U.S., only two of these datasets extend into the Atlantic Ocean and Gulf of Mexico. Therefore, for ecological modeling applications that require information offshore, NARCCAP and Hostetler datasets are the only ones covered in this analysis that have this information for the available variables.

The spatial resolution varies in a similar fashion between downscaled datasets to the domain each covers. Table 3.1 shows that the resolution of NARCCAP is the coarsest (50 km) while the resolution of CLAREnCE10 is the finest (10 km). The resolution of the downscaled datasets created with statistical downscaling (CCR, BCSD, SERAP) falls between NARCCAP and CLAREnCE10. In addition, the Hostetler dataset provides both 15 and 50 km resolution data. Although the spatial resolution varies, the differences between these downscaled datasets and their applications to ecological modeling are discussed in Section 3.5 of this report.

## 3.3 Temporal Resolution and Time Period

All downscaled datasets have information available representing the climate for the 20$^{th}$ and 21$^{st}$ centuries; however, not all datasets have a continuous time series. The BCSD and SERAP datasets cover a continuous period from as early as 1950 (BCSD) to 2099. However, NARCCAP, CLAREnCE10, Hostetler, and CCR do not have a continuous time series of data available (Table 3.1; Figure 3.5). For those analyses investigating differences between future and current climatic change, all six of the downscaled datasets considered in this study can provide information for the available variables. However, if there is a need in an analysis for continuity from the current time to a future period, then the BCSD and SERAP datasets are the only downscaled datasets in this analysis that provide a continous time period. It should also be noted that the output temporal resolution of each of these datasets can be very different. The BCSD dataset has monthly downscaled model output, which is the coursest temporal resolution of all the considered datasets (Table 3.1). SERAP, CCR, and Hostetler provide daily output, while the remaining two datasets (NARCCAP and CLAREnCE10) provide data at hourly, 3-hour, or 6-hour resolution. These different resolutions have implications for what output is available and derivable from each of these datasets, as discussed in the next section.

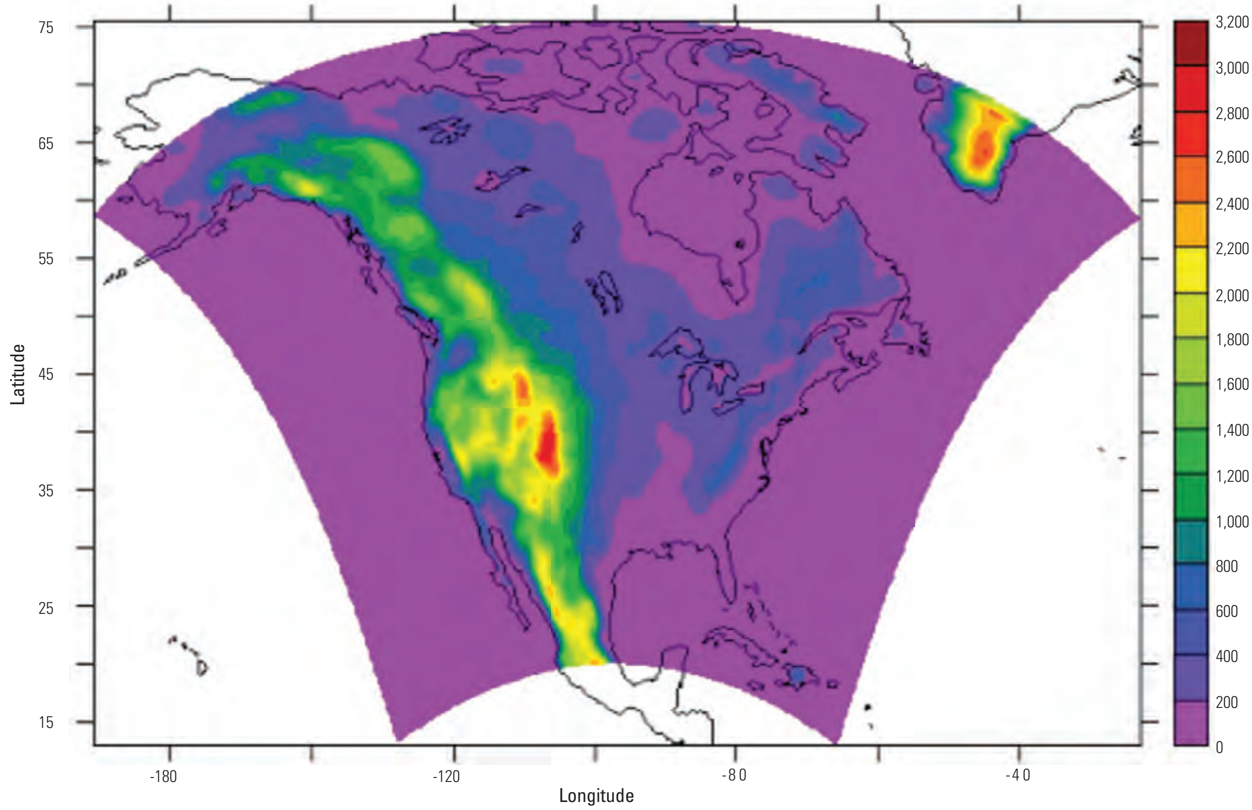


**Figure 3.1.** Model domain of the North American Regional Climate Change Assessment Program (NARCCAP). Original image courtesy of University Corporation for Atmospheric Research (http://www.narccap.ucar.edu/about/index.html).

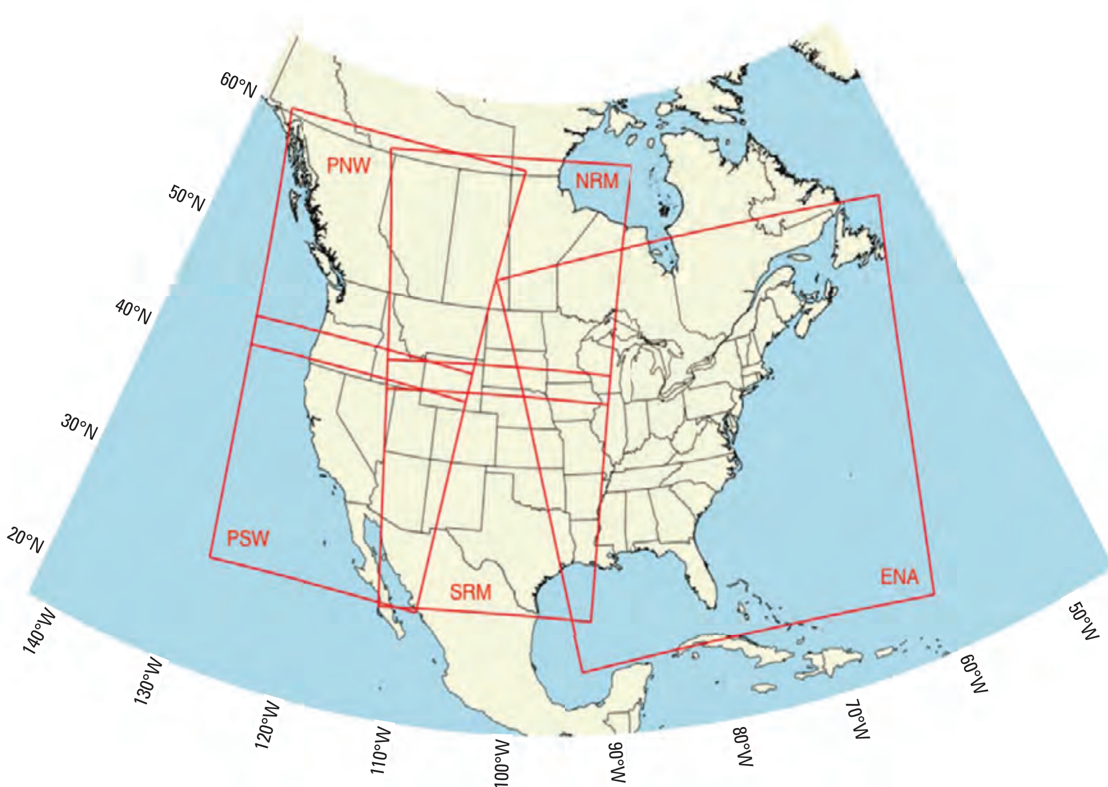


**Figure 3.2.** Modeling domains of the Hostetler datasets. The five model domains: Pacific Northwest (PNW), Pacific Southwest (PSW), Northern Rocky Mountains (NRM), Southern Rocky Mountains (SRM), and Eastern North America (ENA). Original image courtesy of U.S. Geological Survey, Oregon State University (http://regclim.coas.oregonstate.edu/dynamical-downscaling/index.html).

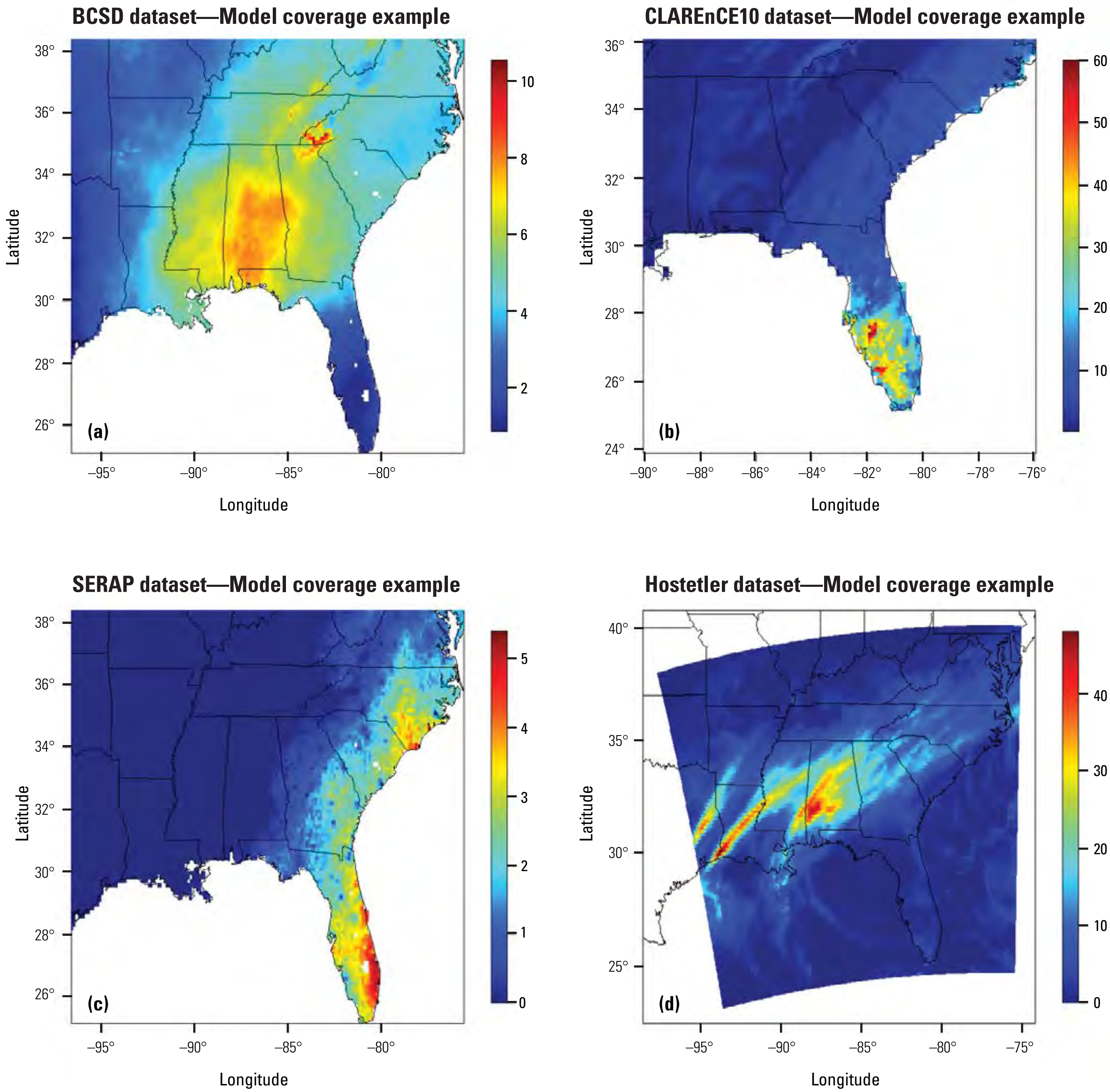


**Figure 3.3.** Model output examples for the (a) Bias Corrected Spatial Disaggregation (BCSD), (b) COAPS Land-Atmospheric Regional Ensemble Climate Change Experiment (CLAREnCE10), (c) Southeast Regional Assessmente Project (SERAP), and (d) Hostetler datasets. BCSD example is for monthly precipitation for Jan. 1960 (mm/day) from CGCM3 with the A1B emissions scenario, CLAREnCE10 example is for daily precipitation for Jan. 1, 2038 (mm) from the HADCM3 with the A2 emissions scenario, SERAP example is for daily precipitation (mm) for Jan. 3, 1960 HADCM3 with the A1B emissions scenario, Hostetler example is daily total precipitation (mm) from Jan. 3, 1980 from the GENMOM model and the A2 emissions scenario.

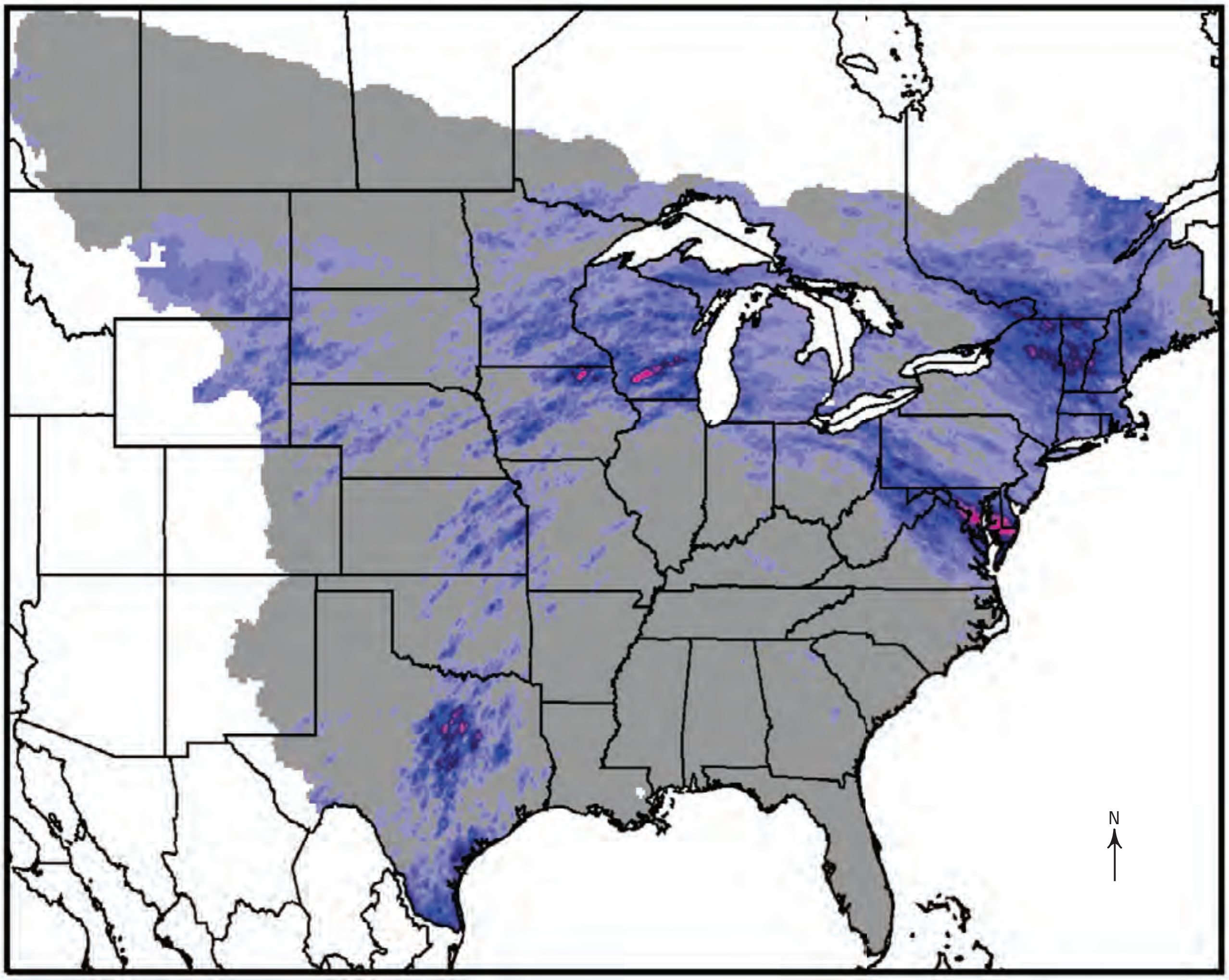


**Figure 3.4.** Domain of model output from the Center for Climatic Research (CCR) dataset. Image courtesy of Dr. David Lorenz (Center for Climatic Research).

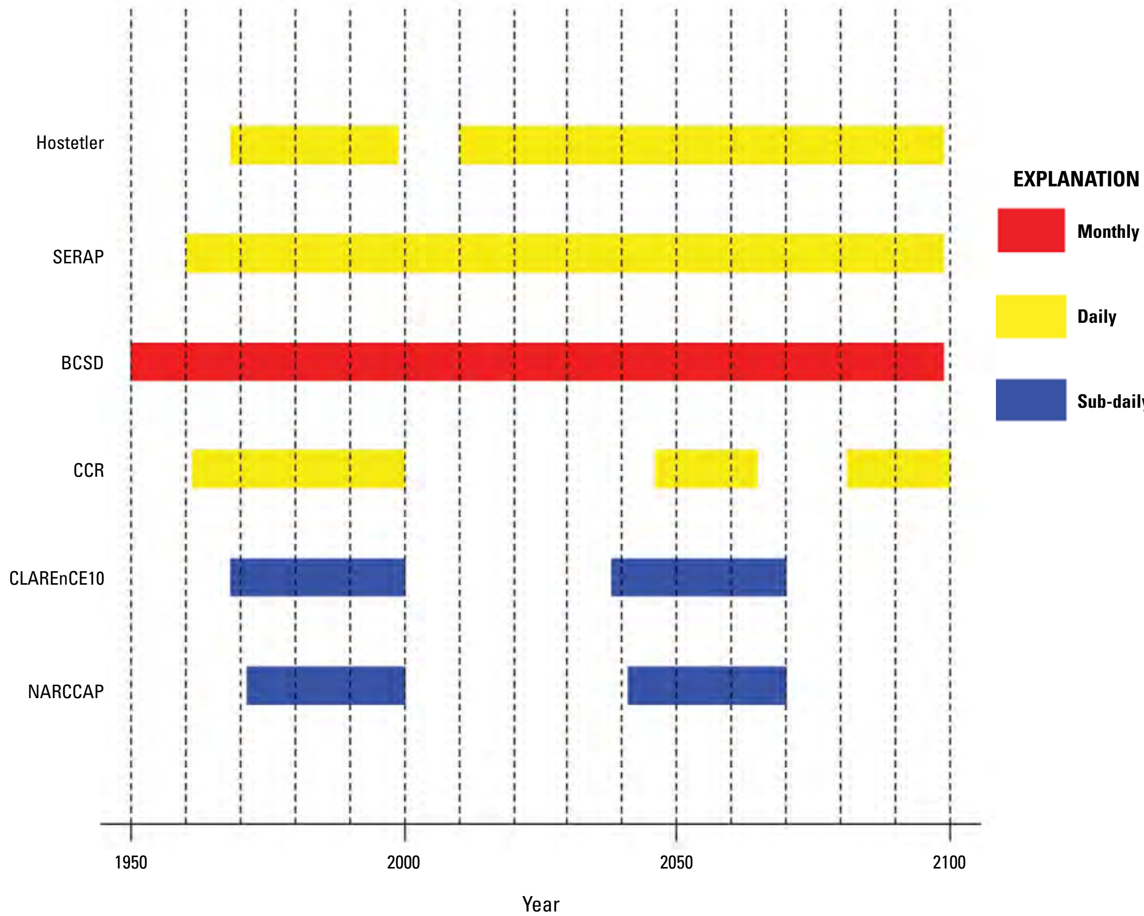


**Figure 3.5.** Output time period for the downscaled datasets.

## 3.4 Available/Derivable Variables

Each of these datasets differs in the specific variables that might be needed for a given application. In this section we will briefly discuss the variables available from each of these datasets both in terms of those used by climate scientists for evaluation and analysis and those used in ecological modeling. The full list of the variables available for each dataset is shown in Table 3.1. In addition, the complete list of variables for NARCCAP is available on the NARCCAP Web site (*http://www.narccap.ucar.edu/data/data-tables.html*).

All the evaluated datasets produce downscaled temperature and precipitation. However, it is important to note that although daily output is available for the SERAP and CCR projects and sub-daily output is available for the dynamic datsets, the BCSD dataset only produces monthly output. This precludes consideration of many derived climate extremes unless additional statistical techniques are employed to simulate sub-monthly values. Temperature and precipitation are the two most commonly downscaled climate variables. Other variables, such as dew point temperature, relative humidity, and wind speed and direction typically are not available from most statistically downscaled datasets, including the SERAP, BCSD, and CCR. The lack of long-term and spatially dense observational records for these variables makes it difficult to build the robust statistical relations necessary for empirical downscaling. Nevertheless, some studies have produced downscaled output for these varibles. Notably, Abatzoglou and Brown (2012) created a downscaled dataset for the Western U.S.that includes temperature, precipitation, wind speed, wind direction, relative humidity, and solar radiation. Information on changes in wind speed and wind direction is not available from the statistically downscaled datasets in this report. The absence of these variables from statistically downscaled datasets also makes it difficult to produce other ecologically important variables such as evapotranspiration. In contrast, dynamic downscaling enables the direct modeling or derivation of these variables.

The Southeast U.S. experiences many different atmospheric circulation patterns at multiple scales, including frontal systems, hurricanes, and sea breezes, all of which influence precipitation, winds, and evapotranspiration at the smaller scales. There are many variables that can be used to define these patterns of circulation, including pressure, vertical motion, and wind speed/direction at high altitudes (Hartmann, 1994; Wallace and Hobbs, 2006). Because dynamically downscaled datasets use equations that represent the physics and dynamics of the atmosphere, some of these features can be resolved or analyzed on the basis of model output. It is less common for statistical downscaling approaches to define patterns of circulation as there is less observed historical data for these variables available to draw the required robust relation.

It is important to note that the statistical techniques represented in these downscaled datasets have been shown by the literature to have difficulty in capturing extremes in temperature and precipitation. As discussed by Wilby and others (2004), transfer functions can underestimate the variability of the variables downscaled, and that is particularly evident with daily precipitation. Variability is tied to frequency of extreme events for the variable in question. For example, underestimated precipitation variability leads to an underestimation of the frequency of extreme wet periods, extreme dry periods, or both. In contrast, if the varability of precipitation is overestimated, there will be a tendency to overestimate the frequency of extreme wet period or extreme dry periods. Some statistical techniques have been applied to improve the representation of extreme events (e.g., Furrer and Katz, 2007). The issues with variability and extreme events in the six downscaled datasets in this analysis will be discussed in Chapter 4.

## 3.5 The Climate Sensitivities of Southeast U.S. Species and Ecosystems

The potential impact associated with changes in precipitation, temperature, and extreme events has led to multiple studies of the impacts to ecosystems in the Southeast and around the world. The National Climate Assessment states that coastal ecosystems in the Southeast will be affected by changes in salinity and water levels associated with sea level rise, and the broader Southeast will be affected by changes in rainfall and evapotranspiration. In addition to these changes, it is also noted that changes in the frequency of fires, hurricanes, and other disturbances can have a profound impact on ecosystems as a whole (Ingram and others, 2013). Specifically in the Southeast, changes in precipitation have been observed during warmer months, causing changes in stream discharges and warmer water (Alexandrov and Hoogenboom, 2001; Rugel and others, 2012).

Two common ecological modeling approaches with regard to climate change include both bioclimatic models and species distribution models. One of the primary concerns with both GCM and downscaled datasets for ecological models is that the spatial scale is too coarse, particularly in mountainous areas. Some studies suggest that the coarse scale of climate models and currently available downscaled datasets cause a bias toward species survivability in the ecosystem models (Trivedi and others, 2008; Franklin and others, 2013). Specifically, Franklin and others (2013) recommend that the resolution of climate model output used be finer than a 4 km spatial resolution, finer than any downscaled dataset in this synthesis. Among the six downscaled datasets evaluated in this report, none come close to this level of spatial resolution (Figure 3.6). Even the finest resolution dataset, CLAREnCE10, has a spatial resolution two to three times as coarse as the recommendations by Franklin and others (2013), while the other datasets are from three to more than ten times as coarse. An example of one such downscaled dataset produced with a resolution finer than 4 km is the NASA Earth Exchange Downscaled Climate Projections (NEX-DCP30; Thrasher and others, 2013). This downscaled dataset has a resolution of 800 meter (m) across the continental U. S. It should be noted, however, NEX-DCP30 is not evaluated here. In addition, while this downscaled dataset does have a finer resolution, the finer resolution does not necessarily indicate that a dataset provides a more accurate representation of historical climate. This in turn does not mean that a finer resolution dataset provides a more accurate representation of future climate. While resolutions finer than 4 km may be desireable or even necessary for some ecological studies, limitations in computing power, scientific knowledge of fine-scale climate processes, and availablility of observed data make the production of downscaled datasets finer than 4km infeasible in most situations.

First, dynamic downscaling requires a large amount of computing power. This leads to a large amount of time (potentially months) and/or a large amount of computer processors required to run the dynamic downscaling. In contrast, the observations that could be used for the creation and evaluation of a dataset created with statistical downscaling typically do not have a resolution finer than 4 km. These are two primary limitations of technology and observations that may be overcome in the future. While it is possible to downscale to these resolutions, there are questions among climatologists as to how meaningful the results would be with regard to the atmospheric processes involved at such fine resolutions. The ability to determine how meaningful downscaling would be at less than 4 km is limited by the availability of measurements at a similar scale to evaluate the resulting downscaled dataset. Therefore, the available computing power limits the amount of downscaling done through a dynamic downscaling process, statistical downscaling is limited by the available observations, and the lack of observations at a resolution as equal to the downscaling limits the ability to assess how meaningful downscaled datasets are at these resolutions.

Although there are limitations to climate observations, there is also a mismatch between the observation record of climate and the measurement records for species and ecosystems. Although the National Climate Assessment Southeast Technical Report (SETR; Ingram and others, 2013) indicates multiple impacts to ecosystems in the Southeast U.S., it also notes (particularly with regard to aquatic ecosystems) that "...the ecological relationships and life histories of many Southeast species are not yet well understood within the constraints of current climatic variability" (p. 243). The SETR has documented numerous studies of the potential impacts of climate change in an effort to show the potential impacts of climate change to Southeast ecosystems. However, although there are studies of climate change impacts to the most vulnerable species, there is no informational database regarding the specific climate sensitivities of individual species. In addition,

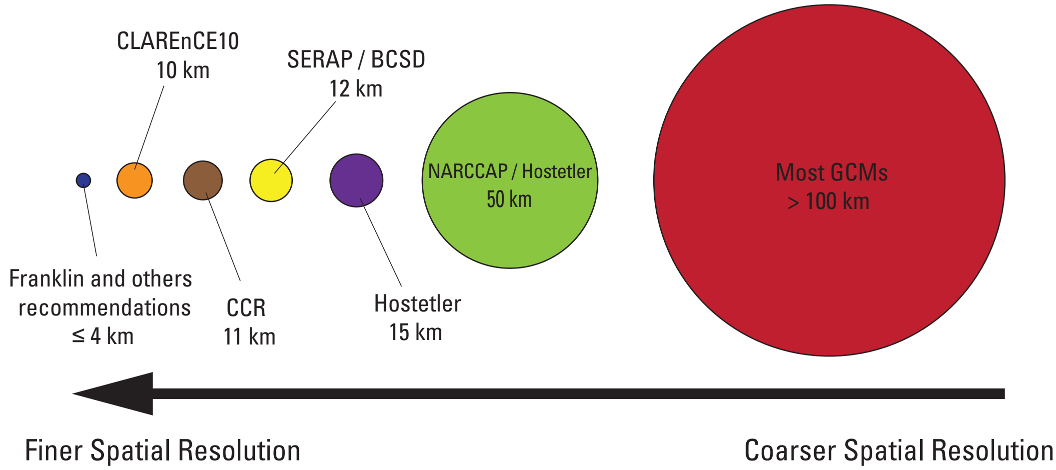


**Figure 3.6.** Visualization of spatial resolution differences between Franklin and others (2013) recommendations, the downscaled datasets, and the global climate models.

although there are more than 100 years of record for weather and climate observations for several locations in the Southeast, there is typically less than 5 years of observations of ecosystems. This mismatch of climate and ecological observations presents a challenge to building robust relations between climate and ecology. In terms of variables available from the downscaled datasets in this synthesis, changes in temperature, precipitation, and the frequency of extreme events (for example, fires, droughts, and hurricanes) are among the most likely aspects of climate change to affect the ecosystems of the Southeast. However, few of the studies described in the SETR describe the climate sensitivities of individual species and the potential impacts. Some examples of species studies include:

- Cabbage Palm and Red Cedar – Desantis and others, 2007
- Bald Cypress – Middleton, 2009
- Cypress and Swamp Gums – Conner and others, 2011
- Multiple Wetland Tree Species – Stallins and others, 2010
- Red and Black Mangroves – Sherrod and others, 1986; Pickens and Hester, 2011
- Longleaf Pine – Bhuta and others, 2009; Stambaugh and others, 2011
- Multiple Freshwater Fish Species – Matthews and Marsh-Matthews, 2003
- Freshwater Mussels – Golladay and others, 2004
- Sea Urchins – Lessios, 1988
- Coral – Jokiel and Coles, 1977; Wilkinson and Souter, 2008
- *Daphnia pulex* and *Daphnia lumholtzi* – Fey and Cottingham, 2011
- *Spartina alterniflora* – Kirwan and others, 2009

While these represent some of the most vulnerable species to climate change in the Southeast, this compilation of studies also allows the opportunity to compare the climate sensitivity of these species. First, consider the sensitivities associated with tree species in the Southeast as shown in Table 3.3. Three of the six species are sensitive to drought conditions, while the remaining three species are sensitive to temperature or a combination of temperature and precipitation. This indicates that there are several climate metrics that can be used to determine the impact of climate change to multiple tree species. All the datasets in this synthesis can provide information on temperature and precipitation and can be used to derive some aspects of future drought conditions. However, while variables such as evapotranspiration can be estimated, the estimate of this variable requires wind speed and solar radiation, neither of which are available from the SERAP, BCSD, and CCR datasets. Table 3.4 shows the sensitivities of the remaining species discussed in the SETR. In this instance, most species are primarily sensitive to changes in water temperature. Given a relation developed between air and water temperature (as in the harmonic analysis by Cho and Lee, 2012), it is possible to estimate water temperature from the available datasets. However, hurricane circulation can only be approximated by the GCMs (Tapiador, 2008), and a hurricane climatology can only be represented by dynamic downscaling techniques (Emanuel and others, 2008). Although a GCM can represent the atmospheric patterns that drive the location of hurricanes, the coarse resolution of a GCM does not allow it to fully resolve the circulation of a hurricane. As such the full circulation and precipitation patterns of a hurricane cannot be resolved by a GCM, though they can be approximated by dynamic downscaling approaches.

**Table 3.3.** Climate sensitivities of given species and associated studies for tree species.

| Species | Study | Sensitivity |
|---|---|---|
| Cabbage Palm | Desantis and others, 2007 | Drought, tidal flooding |
| Southern Red Cedar | Desantis and others, 2007 | Drought, tidal flooding |
| Bald Cypress | Middleton, 2009 | Temperature, precipitation, water depth |
| Multiple Wetland Tree species | Conner and others, 2011 | Drought, precipitation, evapotranspiration |
| Red and Black Mangroves | Sherrod and others, 1986; Pickens and Hester, 2011 | Temperatures < 37.5 F for 2 to 5 days, Temperatures < 20.3 F for 2 to 5 days |
| Longleaf Pine | Bhuta and others, 2009; Stambaugh and others, 2011 | Winter season temperatures and precipitation, fire frequency |

**Table 3.4.** Climate sensitivities of given species and associated studies for the remaining species.

| Species | Study | Sensitivity |
|---|---|---|
| Multiple Freshwater Fish Species | Matthews and Marsh-Matthews, 2003 | Drought |
| Freshwater Mussels | Golladay and others, 2004 | Drought, water temperature |
| Sea Urchins | Lessios, 1988 | Hurricanes, water temperature |
| Coral | Jokiel and Coles, 1977; Wilkinson and Souter, 2008 | Water temperature > 89 F (mortality), Water temperature > 86 F (bleaching), Hurricanes |
| *Daphnia pulex* and *Daphnia lumholtzi* | Fey and Cottingham, 2011 | Temperature, water temperature |
| *Spartina alterniflora* | Kirwan and others, 2009 | Mean annual temperature |

Although the literature on the climate sensitivities of species continues to grow, it remains a challenge for climatologists to provide downscaled datasets that speak to the great complexity and diversity of relations between species, their ecosystems, and climate. In addition to the computational expense associated with running GCMs and downscaling, there is also a computing issue associated with storage. The results of running a GCM and downscaling process can lead to the production of several terrabytes (or in the case of GCMs used for IPCC, petabytes). Therefore, even though there are many variables produced by a GCM and downscaling, only some of them can be stored. Without knowledge of which climate variables and associated thresholds are important, the variables stored will be chosen by the climate modeler without emphasis on the needs of other disciplines. In addition, the lack of knowledge regarding the sensitivity limits the ability to assess the accuracy of downscaled datasets for the critical needs of ecologists for a specific species or habitat.

# 4 Downscaled Dataset Evaluation

This section describes the results of an initial evaluation of each of the downscaled datasets described in this report for ecosystem modeling across the Southeast U.S. The methodology for this initial evaluation is discussed in Section 4.1, followed by a summary of results and a discussion of several key points common to multiple downscale datasets in Section 4.2.

## 4.1 Data and Methods

Each of the six downscaled datasets has distinct differences in metadata, which presents unique challenges for evaluating model output across the Southeast. Each dataset has a different spatial resolution, temporal resolution, time period (or periods), and spatial domain. In order to focus on the differences between the downscaled datasets rather than those caused by differences in scale and methodology, the evaluation was done over scales, periods, and domains common to all six datasets. Specifically, this method considers all the variables evaluated for each downscaled dataset over the following scales, periods, and spatial domains:

- **Temporal resolution—**For this initial evaluation the variables in the evaluation were considered at a monthly timescale. Given that the BCSD dataset has only a monthly temporal resolution, the remaining datasets were aggregated to this temporal resolution.
- **Time period—**The datasets were evaluated over a historical time period that is common to all six datasets and to the observed gridded dataset used for this evaluation. The time period chosen is 1971 through 1999.
- **Spatial resolution—**Given that NARCCAP has the coarsest resolution of these downscaled datasets, the five remaining downscaled datasets and the observed dataset were aggregated to the resolution of NARCCAP (50 km). However, given the potential value of an evaluation on a finer scale, an additional level of analysis used a 15 km resolution and excluded NARCCAP from analysis.

- **Spatial domain—**The continental portion of the Southeast Climate Science Center (SECSC) domain was the basis for this evaluation. The latitude/longitude boundaries used for this domain are 25N to 38N and 94W to 75W. However, given the variations in topography and climatic conditions across the study domain, several regional subdomains were also used for this evaluation. These domains are discussed in more depth below.

Figure 4.1 shows the boundaries of the regional subdomains used in this evaluation, and Table 4.1 lists the number, name, and latitude/longitude boundaries of each subdomain in the Southeast U.S. These subdomains are used in assessing the performance of each of the six datasets during a historical period. Note that CLAREnCE10 does not cover the entire study domain. CLAREnCE10 extends to 37N and 89W, which excludes all or parts of subdomains 8 through 14. As such, the five remaining datasets were evaluated for subdomains 8 through 14, and CLAREnCE10 was excluded from the analyses for these subdomains. The subdomains were chosen at their respective sizes and shapes to capture the different microclimates across the Southeast U.S.

### 4.1.1 Observed Dataset

PRISM (Parameter-elevation Regression on Independent Slopes Model) is a 4 km monthly modeled dataset created from station observations covering the continental U.S. PRISM data are derived using a spatial model that uses point data, a digital elevation model, and other spatial datasets to generate gridded estimates of annual, monthly, and event-based climatic elements. The spatial modeling of PRISM involves a coordinate set of rules that takes into account elevation and proximity to water. Full details regarding PRISM are available from Daly and others (2008), and further documentation is available on the PRISM Web site. The specific PRISM dataset used to evaluate the downscaled datasets here is the AN81m monthly data with a spatial resolution of 2.5 minutes

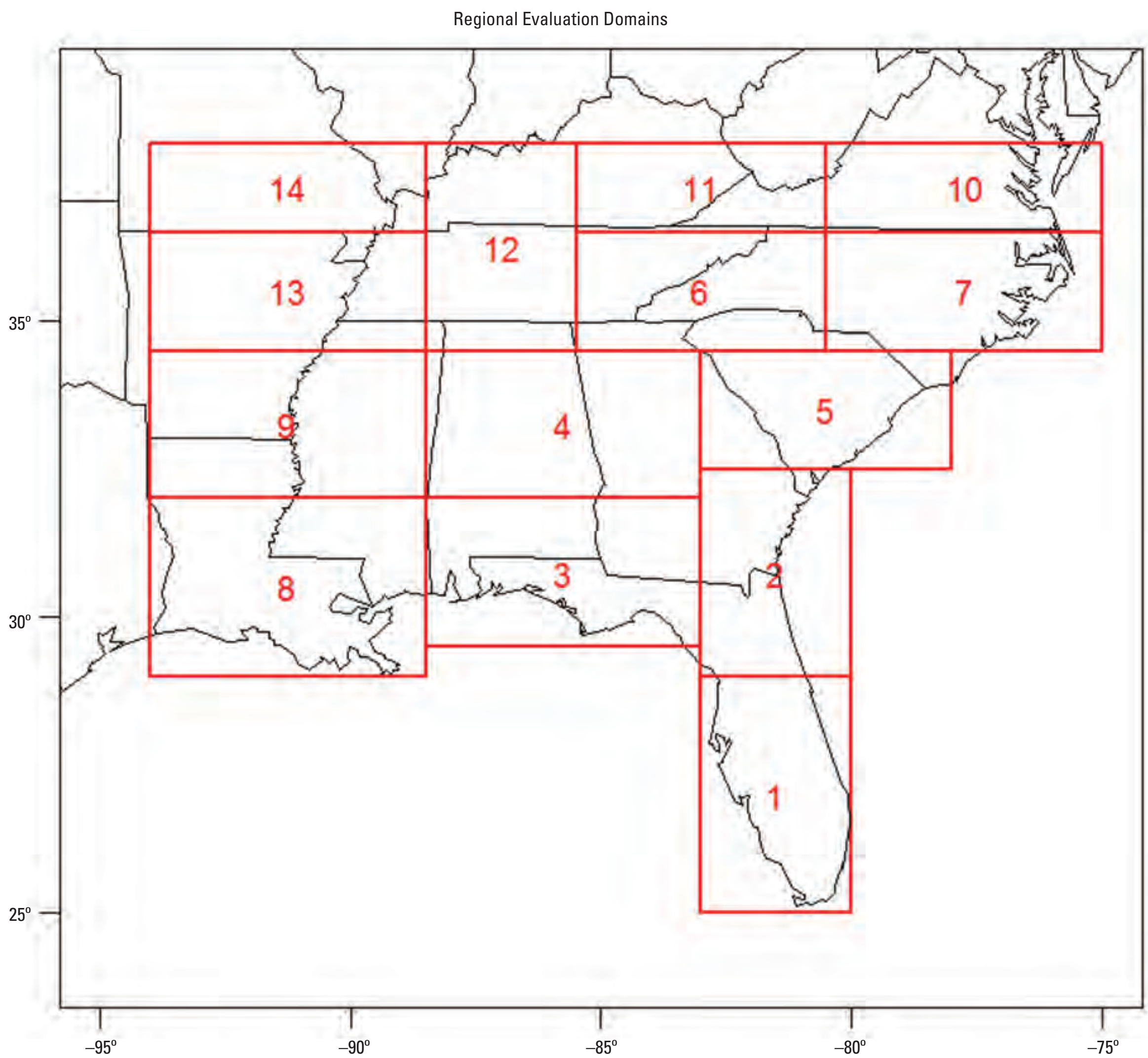


**Figure 4.1.** Map of regions used in evaluation.

(approximately 4 km), which was also aggregated to a 50 km resolution for the evaluation (PRISM Climate Group, 2014). It is important to acknowledge that although PRISM is created with observed data, it does have some errors that are associated with the spatial modeling used to create it. However, these errors are considered negligible compared to the errors of downscaled datasets themselves. It should also be noted, that PRISM was not used in the creation of any of the downscaled datasets in this analysis.

### 4.1.2 GCM Constraints

This initial evaluation compares the downscaled data from the Geophysical Fluid Dynamics Lab (GFDL) GCM only. An evaluation of the ensemble of all available downscaled GCMs for each dataset was considered; however, the statistically downscaled datasets SERAP, BCSD, and CCR have downscaled data from more GCMs than dynamically downscaled datasets such as NARCCAP, Hostetler, and CLAREnCE10. Given that GFDL is the only GCM in common among all of the downscaled datasets, only the evaluation based on downscaled GFDL data is presented here. It is important to note that a comprehensive comparison of GCMs was beyond the scope of this project; however, a comparison of GCMs is available from Sheffield and others (2013).

### 4.1.3 GFDL Contraints

In previous sections, it was mentioned that GCMs have their own biases before the data are downscaled. Given that each downscaled dataset evaluated in this report is derived GFDL GCM data, the datasets all inherit the errors from that GCM. GFDL's simulated interannual surface temperature variability appears excessive over the Southeast U.S. (Knutson and others, 2006). In addition, GFDL has a cold bias for annual mean temperature. GFDL-modeled annual average temperatures in the Southeast U.S. are 1 to 5 °C below the average observations for the year (Delworth and others, 2006). The GFDL-modeled annual temperature is more variable than observations in the U.S., especially along the Gulf Coast. Furthermore, the GCM has a dry bias along the Gulf Coast and over Florida; however, the model becomes wetter than observations over North Carolina. Although the datasets in this synthesis all downscale GFDL, they do not all downscale the same model version. Hostetler and CCR downscale GFDL model version 2.0 while CLAREnCE10 and NARCCAP downscale GFDL model version 2.1. The remaining datasets, SERAP and BCSD, downscale both model versions 2.0 and 2.1; however, only the downscaled data from GFDL model version 2.1 were analyzed in this synthesis (Table 3.1). Differences in modeled temperature and precipitation between the two versions of GFDL downscaled in the evaluated datasets are due to changes in model parameterizations. The temperature in GFDL model version 2.0, downscaled in CCR and Hostetler, is approximately one degree cooler in the Southeast U.S. except for in the State of Florida (Delworth and others,2006). GFDL version 2.0 temperature is less variable than the temperature in GFDL version 2.1 by approximately 0.1 standard deviations. The anomalously dry region along the Gulf Coast extends further north in GFDL version 2.1 than in GFDL version 2.0. Model version 2.1 of GFDL is similar to model version 2.0; however, there are differences in parameterizations of clouds and the land surface, as well as a change in dynamic equations. Model version 2.1 was calibrated to substantially reduce an equatorward drift in winds in the midlatitudes and the global cold bias that exist in model version 2.0 (Delworth and others, 2006). The errors identified in the GFDL GCM over the Southeast U.S. do not suggest that the model is inadequate for use as input to regional downscaling; however, users of downscaled products need to be aware of such issues in order to understand and adequately interpret results from downscaling methods. Images and statistical evaluation of other downscaled GCMs from the downscaled datasets will be made available through the SECSC, but they are not discussed in this report.

### 4.1.4 Variables and Evaluation Metrics

Two climate variables, monthly average temperature and precipitation, were chosen for the initial evaluation. These variables were chosen because they were among the highest priority variables requested by ecologists at a workshop held on May 16–17, 2013, in Raleigh, N.C. This workshop highlighted temperature, precipitation, winds, and evapotranspiration as a common set of variables of interest to ecologists. It is also important to ecologists to consider how a downscaled dataset represents the average, variability, and extremes of each variable (see Appendix 1 for a summary of the findings of the workshop). Here, we evaluated the following metrics:

- **Bias** was used to assess differences between the mean of each variable for each month from the observations during the historical period. Bias for each variable for each month was represented as

  $$Bias_i = D_i - O,$$

  where $i$ is the dataset; $D_i$ is the mean of the variable during the historical period; and $O$ is the observed mean of the variable during the historical period. This bias was considered across the time period over the domain. This metric was used to assess what amount of bias is present in the downscaled datasets that are available, regardless of if these downscaled datasets have had bias correction applied.

- **Standard Deviation Difference** was used to assess differences in the year to year variability of temperature and precipitation between each dataset and the observations. This difference is calculated similarly to the bias. However, instead of considering the mean of each variable from each dataset and the observations, the standard deviation was calculated for each variable for each dataset and the observations. These were then used to determine the standard deviation difference. This difference was considered across the time period over the domain. The standard deviation difference is analogous to how each downscaled dataset represents the natural variability of a given variable. A downscaled dataset that underestimates the variability of precipitation (i.e., a negative standard deviation difference) indicates that the downscaled dataset in question has as many very wet or very dry periods as observed historically.

- **Probability Distribution Functions** – Given that different species and landscapes are affected by different thresholds of temperature and precipitation extremes, the probability distribution functions (PDFs) for each dataset and the observations are used to assess differences in the representation of these extremes. The PDFs are calculated for January and July for each of the subregions in the Southeast U.S. domain. The PDFs estimated by each downscaled dataset to the observed PDF allows for an assessment of how frequently given thresholds of temperature and precipitation occur compared to observations. Given that different thresholds of temperature and preciptitation influence different species, comparing these PDFs to observed PDFs provides sense of the accuracy of each downscaled dataset for multiple thresholds of importance.

- **Annual Cycle** – The annual cycle of a variable is defined as the fluctuation of the variable that is a function of the time of year (American Meteorological Society, 2000). In addition to a qualitative comparison of the annual cycles, the root mean square error and correlation are calculated for each dataset and variable. Root mean square error is a measure of the difference between the model and the observations. Higher values indicate greater differences beween the models and the observations. Correlation is a measure of the relation between the annual cycle from each downscaled dataset and the observed annual cycle. For instance, if the observed temperature increases from winter to summer by 10 degrees, will the temperatures estimated by each downscaled dataset increase by a similar amount? This is all related to how well each downscaled dataset replicates the timing and transition between seasons for temperature and precipitation, which is critical for the phenology of species and ecosystems.

Given the methodology and constraints, the next section discusses the results of this initial evaluation. The final section discusses the broad conclusions of this study and recommendations for dataset use and future research.

## 4.2 Results and Discussion

Given the large amount of information available from each downscaled dataset, the results presented in this section are divided into two subsections. The first subsection summarizes the overall results for each subregion in the domain. The second subsection discusses important aspects of the evaluation and comparison of these downscaled datasets to consider prior to use in ecological modeling and decisionmaking.

### 4.2.1 Summary of Results

Results for each region described in Table 4.1 are summarized in Tables 4.2–4.15. The tables are organized in order for subdomains 1–14. The downscaled datasets are each one column in a table. The metrics evaluated are listed in the rows. Each cell of the table lists the value of the relative error of the variable for the given month for the downscaled dataset listed at the top of the column. The relative error for each downscaled dataset and variable was defined as

$$\delta x = \frac{x}{x_0} - 1$$

where $\delta x$ is the relative error; $x$ is the value of a given variable estimated by any given downscaled dataset; and $x_0$ is the observed value of the given variable as indicated by PRISM. Positive (or negative) values of the relative error indicate that a variable is overestimated (or underestimated) by a downscaled dataset. In Tables 4.2–4.15, the relative error for each variable (average temperature, temperature variability, average precipitation, and precipitation variability) is shown monthly and color coded for each downscaled dataset. The relative error is included in addition to the other metrics described to summarize the results of the full analysis. The complete analyses for all metrics is included in Appendixes 2, 3, and 4. Relative error gives an indication of how well a variable is estimated by a downscaled dataset relative to the observed value of that variable.

**Average Temperature:** The dynamic datasets, CLAREnCE10, Hostetler, and NARCCAP, have relative errors that indicate a consistent cold bias throughout the year in most regions (Tables 4.2–4.15). However, CLAREnCE10 has a warm bias during July and August in Southern Florida, Northern Gulf Coast of Florida, and Alabama/Western Georgia (Tables 4.2, 4.4, 4.5). CLAREnCE10 temperatures are closer to observed temperatures than the other dynamic datasets for all seasons in most regions with the exception of winter in the Southern Appalachians (Table 4.7). There is a warm bias to the west of the Appalachians and a cold bias on the eastern side of the mountains in all downscaled datasets created with statistical downscaling in all months. An example of this is shown in the bias maps for January (Figure 4.2). It is important to note that this mountain bias is also present in the downscaled datasets created with dynamic downscaling when bias correction is applied.

**Table 4.1.** Regional subdomain information.

| Subdomain number | Subdomain name | Minimum latitude | Maximum latitude | Minimum longitude | Maximum longitude |
|---|---|---|---|---|---|
| 1 | Southern Florida | 25 | 29 | –83 | –80 |
| 2 | Northeast Florida / Georgia Coast | 29 | 32.5 | –83 | –80 |
| 3 | Northern Gulf Coast of Florida | 29.5 | 32 | –88.5 | –83 |
| 4 | Alabama / Western Georgia | 32 | 34.5 | –88.5 | –83 |
| 5 | South Carolina | 32.5 | 34.5 | –83 | –79 |
| 6 | Southern Appalachians | 34.5 | 36.5 | –85.5 | –80.5 |
| 7 | Eastern North Carolina | 34.5 | 36.5 | –80.5 | –75 |
| 8 | Louisiana / Mississippi Coast | 29 | 32 | –94 | –88.5 |
| 9 | Northern Mississippi / Northern Louisiana / Southern Arkansas | 32 | 34.5 | –94 | –88.5 |
| 10 | Southeast Virginia | 36.5 | 38 | –80.5 | –75 |
| 11 | Western Virginia / Eastern Kentucky | 36.5 | 38 | –85.5 | –80.5 |
| 12 | Western Kentucky / Tennessee | 34.5 | 38 | –88.5 | –85.5 |
| 13 | Northern Arkansas | 34.5 | 36.5 | –94 | –88.5 |
| 14 | Southern Missouri | 36.5 | 38 | –94 | –88.5 |

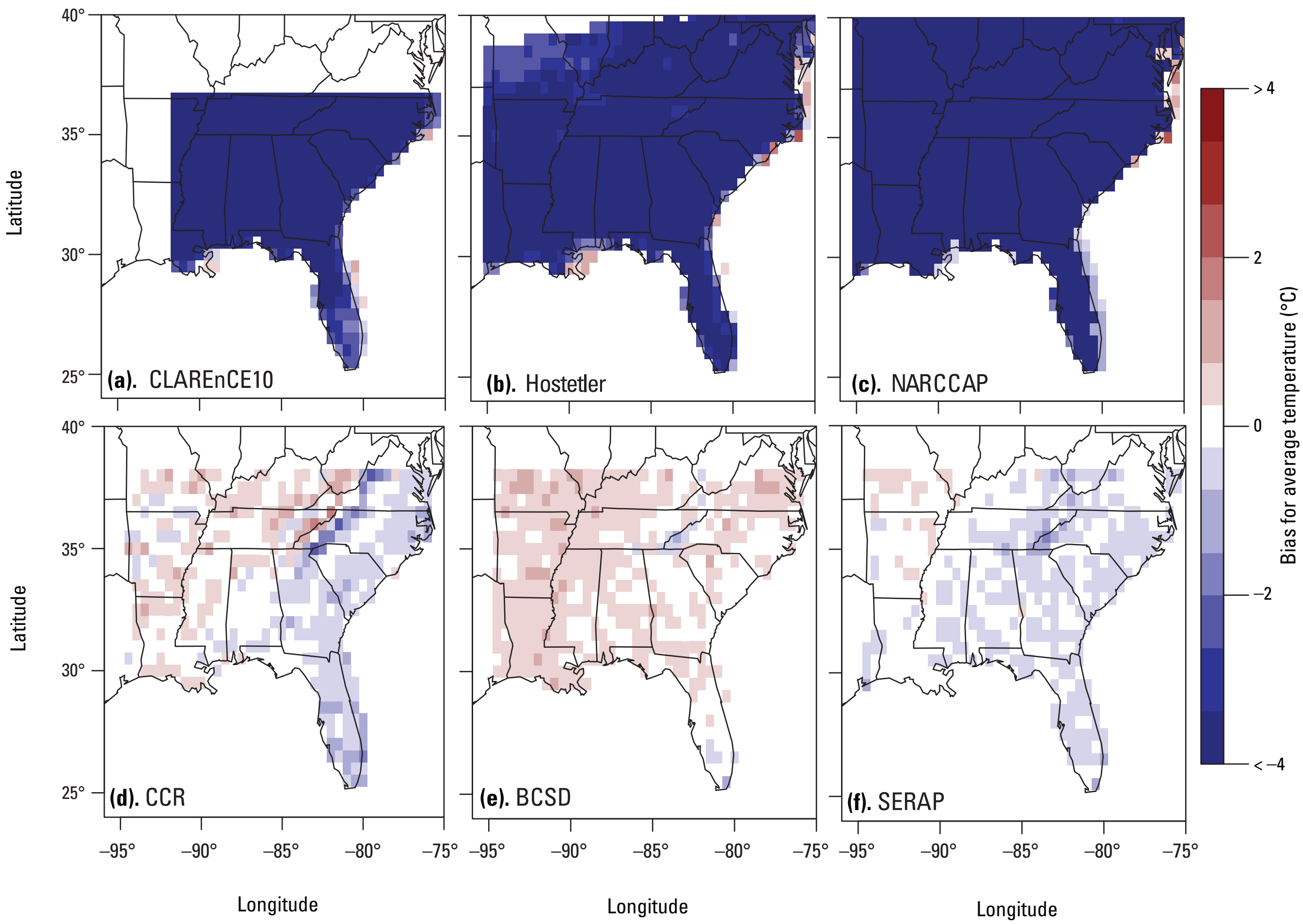


**Figure 4.2.** Bias for monthly average temperature (°C) in January for (a) CLAREnCE10, (b) Hostetler, (c) NARCCAP, (d) CCR, (e) BCSD, and (f) SERAP.

**Table 4.2.** Summary of results for Region 1–Southern Florida, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

| Month | Average temperature | | | | | | Temperature variability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP |
| Jan. | –0.10 | –0.20 | –0.26 | –0.01 | –0.02 | –0.04 | 0.07 | –0.13 | –0.06 | –0.22 | –0.14 | –0.15 |
| Feb. | –0.13 | –0.22 | –0.26 | –0.01 | –0.02 | –0.02 | 0.26 | 0.07 | 0.18 | 0.06 | 0.05 | 0.13 |
| Mar. | –0.13 | –0.22 | –0.25 | 0.00 | –0.01 | –0.01 | 0.30 | 0.14 | 0.29 | 0.07 | –0.01 | 0.15 |
| Apr. | –0.09 | –0.18 | –0.20 | –0.01 | –0.00 | –0.01 | 0.18 | 0.08 | –0.01 | 0.07 | –0.04 | 0.03 |
| May | –0.06 | –0.18 | –0.19 | –0.00 | 0.00 | –0.01 | 0.03 | –0.00 | –0.08 | –0.20 | –0.25 | –0.14 |
| June | –0.02 | –0.16 | –0.17 | –0.01 | –0.00 | –0.00 | 0.11 | 0.58 | 0.02 | –0.02 | 0.06 | 0.03 |
| July | 0.01 | –0.12 | –0.11 | –0.00 | 0.00 | 0.01 | 0.53 | 1.29 | 1.04 | –0.01 | –0.11 | 0.53 |
| Aug. | 0.01 | –0.13 | –0.11 | 0.00 | 0.00 | 0.00 | 0.77 | 1.30 | 0.84 | 0.18 | –0.05 | 0.61 |
| Sept. | –0.03 | –0.16 | –0.14 | 0.00 | –0.00 | –0.00 | 0.79 | 0.46 | 0.68 | 0.06 | 0.03 | 0.41 |
| Oct. | –0.03 | –0.16 | –0.15 | –0.01 | –0.02 | –0.01 | 0.31 | –0.01 | 0.19 | 0.06 | 0.04 | 0.18 |
| Nov. | –0.04 | –0.17 | –0.20 | –0.04 | –0.04 | –0.02 | 0.41 | 0.10 | 0.18 | –0.06 | 0.05 | –0.04 |
| Dec. | –0.07 | –0.18 | –0.24 | –0.02 | –0.04 | –0.03 | 0.32 | –0.03 | 0.16 | –0.05 | –0.02 | –0.00 |

| EXPLANATION | |
|---|---|
| From | To |
| < | –0.80 |
| –0.80 | –0.50 |
| –0.50 | –0.30 |
| –0.30 | –0.10 |
| –0.10 | 0.10 |
| 0.10 | 0.30 |
| 0.30 | 0.50 |
| 0.50 | 0.80 |
| > | 0.80 |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP |
| Jan. | 1.02 | 0.26 | 0.55 | –0.09 | –0.07 | 0.03 | 0.72 | –0.11 | 0.14 | –0.17 | –0.11 | –0.08 |
| Feb. | 0.61 | 0.15 | 0.52 | –0.13 | 0.10 | –0.01 | 0.21 | –0.30 | –0.10 | –0.21 | –0.07 | –0.06 |
| Mar. | 0.34 | 0.01 | 0.41 | –0.04 | –0.02 | –0.08 | 0.08 | –0.35 | –0.07 | –0.09 | –0.09 | –0.09 |
| Apr. | 0.24 | 0.40 | 0.62 | 0.04 | 0.07 | 0.18 | –0.06 | –0.09 | 0.12 | –0.04 | –0.11 | 0.14 |
| May | –0.05 | 0.20 | 0.32 | –0.07 | –0.02 | –0.05 | 0.03 | –0.14 | 0.02 | 0.13 | –0.06 | 0.42 |
| June | –0.42 | –0.22 | –0.23 | –0.03 | –0.00 | 0.09 | –0.24 | –0.38 | –0.38 | 0.07 | –0.11 | 0.58 |
| July | –0.13 | –0.11 | 0.04 | 0.05 | 0.01 | 0.01 | 0.22 | 0.11 | 0.73 | 0.51 | –0.20 | 0.83 |
| Aug. | 0.11 | 0.02 | 0.21 | 0.01 | –0.02 | –0.02 | 0.37 | 0.27 | 0.95 | 0.25 | –0.27 | 0.38 |
| Sept. | 0.45 | 0.07 | 0.31 | –0.04 | 0.09 | 0.16 | 0.40 | 0.00 | 0.52 | 0.15 | –0.13 | 0.45 |
| Oct. | 1.05 | 0.07 | 0.81 | –0.10 | 0.21 | 0.14 | 0.78 | –0.04 | 0.57 | –0.13 | 0.12 | 0.25 |
| Nov. | 1.01 | –0.18 | 0.22 | –0.15 | –0.10 | –0.17 | 0.77 | –0.28 | 0.07 | –0.24 | –0.20 | –0.15 |
| Dec. | 1.34 | 0.27 | 0.92 | 0.03 | 0.15 | 0.18 | 0.41 | –0.33 | –0.02 | –0.17 | –0.13 | –0.11 |

| EXPLANATION | |
|---|---|
| From | To |
| < | –0.80 |
| –0.80 | –0.50 |
| –0.50 | –0.30 |
| –0.30 | –0.10 |
| –0.10 | 0.10 |
| 0.10 | 0.30 |
| 0.30 | 0.50 |
| 0.50 | 0.80 |
| > | 0.80 |

**Table 4.3.** Summary of results for Region 2–Northeast Florida/Georgia Coast, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

| Month | Average temperature | | | | | | Temperature variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | –0.17 | –0.35 | –0.44 | 0.02 | –0.00 | –0.05 | 0.36 | –0.04 | –0.10 | –0.21 | –0.14 | –0.17 | < | –0.80 |
| Feb. | –0.19 | –0.33 | –0.40 | –0.00 | –0.01 | –0.00 | 0.59 | 0.21 | 0.21 | 0.11 | 0.08 | 0.15 | –0.80 | –0.50 |
| Mar. | –0.18 | –0.29 | –0.34 | –0.00 | –0.02 | –0.03 | 0.37 | 0.11 | 0.18 | 0.16 | 0.09 | 0.23 | –0.50 | –0.30 |
| Apr. | –0.11 | –0.22 | –0.23 | –0.01 | 0.00 | –0.01 | 0.41 | 0.26 | 0.12 | 0.19 | 0.06 | 0.26 | –0.30 | –0.10 |
| May | –0.08 | –0.20 | –0.19 | 0.01 | 0.01 | –0.00 | 0.13 | –0.03 | –0.02 | –0.00 | –0.04 | –0.03 | –0.10 | 0.10 |
| June | –0.02 | –0.19 | –0.17 | 0.00 | 0.00 | 0.00 | –0.05 | –0.35 | –0.29 | –0.17 | –0.02 | –0.11 | 0.10 | 0.30 |
| July | 0.01 | –0.17 | –0.12 | –0.00 | 0.00 | 0.00 | 0.71 | 0.11 | 0.97 | 0.10 | –0.04 | 0.59 | 0.30 | 0.50 |
| Aug. | 0.01 | –0.16 | –0.12 | 0.00 | 0.00 | 0.01 | 0.72 | 0.12 | 0.55 | 0.35 | 0.05 | 0.73 | 0.50 | 0.80 |
| Sept. | –0.02 | –0.17 | –0.15 | 0.00 | –0.01 | –0.01 | 0.70 | 0.17 | 0.20 | 0.13 | 0.10 | 0.44 | > | 0.80 |
| Oct. | –0.01 | –0.17 | –0.15 | –0.00 | –0.02 | –0.01 | 0.46 | 0.03 | 0.01 | 0.03 | –0.03 | 0.14 | | |
| Nov. | –0.03 | –0.20 | –0.25 | –0.03 | –0.05 | –0.02 | 0.65 | 0.10 | –0.02 | –0.12 | 0.01 | –0.05 | | |
| Dec. | –0.13 | –0.29 | –0.40 | –0.03 | –0.05 | –0.05 | 0.73 | 0.07 | 0.05 | –0.06 | 0.01 | –0.02 | | |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | 0.62 | –0.03 | 0.01 | –0.18 | –0.09 | –0.10 | 0.19 | –0.17 | –0.18 | –0.18 | –0.02 | –0.18 | | |
| Feb. | 0.44 | –0.08 | 0.27 | 0.06 | 0.11 | 0.15 | 0.14 | –0.25 | –0.01 | 0.13 | –0.14 | –0.08 | | |
| Mar. | 0.39 | –0.12 | 0.11 | 0.03 | 0.03 | 0.04 | 0.33 | –0.21 | 0.00 | 0.08 | –0.07 | –0.04 | < | –0.80 |
| Apr. | 0.65 | 0.41 | 0.42 | 0.11 | 0.05 | 0.14 | 0.24 | –0.00 | 0.21 | 0.09 | –0.18 | –0.14 | –0.80 | –0.50 |
| May | 0.11 | 0.15 | 0.28 | –0.07 | 0.00 | –0.04 | 0.11 | –0.20 | 0.07 | 0.08 | –0.15 | 0.25 | –0.50 | –0.30 |
| June | –0.27 | –0.17 | –0.02 | 0.02 | 0.01 | 0.02 | –0.01 | –0.36 | 0.12 | 0.31 | –0.20 | 0.51 | –0.30 | –0.10 |
| July | –0.03 | –0.01 | 0.04 | 0.03 | 0.05 | 0.10 | 0.35 | –0.13 | 0.69 | 0.76 | –0.11 | 1.00 | –0.10 | 0.10 |
| Aug. | –0.03 | –0.18 | –0.09 | 0.02 | 0.01 | 0.04 | 0.06 | –0.30 | 0.24 | 0.27 | –0.15 | 0.33 | 0.10 | 0.30 |
| Sept. | 0.42 | –0.22 | –0.11 | 0.06 | 0.04 | 0.06 | 0.29 | –0.26 | 0.05 | 0.30 | –0.11 | 0.20 | 0.30 | 0.50 |
| Oct. | 0.65 | –0.24 | 0.15 | –0.14 | –0.00 | –0.09 | 0.46 | –0.26 | 0.14 | –0.27 | –0.04 | –0.08 | 0.50 | 0.80 |
| Nov. | 1.05 | –0.13 | 0.11 | –0.17 | –0.13 | –0.07 | 1.04 | –0.10 | –0.01 | –0.11 | –0.24 | –0.22 | > | 0.80 |
| Dec. | 1.27 | 0.32 | 0.61 | 0.05 | –0.02 | 0.14 | 0.41 | 0.02 | –0.04 | –0.10 | –0.19 | –0.12 | | |

**Table 4.4.** Summary of results for Region 3—Northern Gulf Coast of Florida, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

| Month | Average temperature | | | | | | Temperature variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | –0.40 | –0.43 | –0.56 | 0.05 | 0.02 | –0.04 | 0.17 | –0.10 | –0.16 | –0.22 | –0.23 | –0.19 | < | –0.80 |
| Feb. | –0.33 | –0.37 | –0.48 | 0.01 | 0.01 | 0.02 | 0.69 | 0.39 | 0.35 | 0.24 | 0.19 | 0.27 | –0.80 | –0.50 |
| Mar. | –0.24 | –0.31 | –0.37 | –0.00 | –0.02 | –0.03 | 0.37 | 0.14 | 0.17 | 0.20 | 0.10 | 0.25 | –0.50 | –0.30 |
| Apr. | –0.11 | –0.21 | –0.24 | –0.01 | 0.01 | –0.00 | 0.41 | 0.18 | 0.10 | 0.14 | 0.09 | 0.19 | –0.30 | –0.10 |
| May | –0.06 | –0.19 | –0.19 | 0.01 | 0.02 | –0.00 | 0.20 | –0.07 | 0.02 | 0.00 | 0.02 | 0.07 | –0.10 | 0.10 |
| June. | –0.02 | –0.19 | –0.16 | 0.00 | 0.01 | –0.00 | 0.05 | –0.23 | –0.21 | –0.03 | 0.03 | –0.03 | 0.10 | 0.30 |
| July | 0.04 | –0.16 | –0.10 | –0.00 | 0.00 | 0.01 | 1.08 | 0.54 | 1.27 | 0.20 | –0.06 | 0.59 | 0.30 | 0.50 |
| Aug. | 0.03 | –0.16 | –0.10 | 0.01 | 0.00 | 0.01 | 0.90 | 0.21 | 0.69 | 0.33 | 0.09 | 0.59 | 0.50 | 0.80 |
| Sept. | –0.03 | –0.19 | –0.15 | 0.01 | –0.01 | –0.01 | 0.60 | 0.04 | 0.17 | 0.11 | 0.03 | 0.40 | > | 0.80 |
| Oct. | –0.06 | –0.19 | –0.17 | 0.00 | –0.01 | –0.01 | 0.41 | 0.06 | 0.08 | 0.03 | –0.06 | 0.24 | | |
| Nov. | –0.14 | –0.23 | –0.30 | –0.03 | –0.04 | –0.01 | 0.47 | 0.09 | –0.08 | –0.11 | –0.01 | –0.03 | | |
| Dec. | –0.35 | –0.37 | –0.52 | –0.03 | –0.03 | –0.06 | 0.50 | –0.04 | –0.02 | –0.09 | –0.00 | –0.03 | | |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | 0.01 | –0.25 | –0.19 | –0.25 | –0.10 | –0.12 | –0.01 | –0.26 | –0.21 | –0.06 | –0.03 | –0.16 | | |
| Feb. | –0.08 | –0.26 | –0.04 | 0.07 | 0.03 | 0.16 | –0.04 | –0.30 | –0.10 | 0.28 | –0.05 | 0.23 | | |
| Mar. | 0.12 | –0.21 | –0.20 | 0.04 | 0.01 | –0.04 | 0.32 | –0.13 | –0.19 | 0.33 | –0.12 | 0.01 | < | –0.80 |
| Apr. | 0.69 | 0.44 | 0.43 | 0.03 | 0.12 | 0.17 | 0.34 | 0.13 | 0.07 | 0.06 | –0.12 | –0.11 | –0.80 | –0.50 |
| May | 0.13 | 0.16 | 0.25 | –0.16 | –0.11 | –0.18 | –0.04 | –0.21 | –0.06 | 0.04 | –0.26 | 0.04 | –0.50 | –0.30 |
| June. | –0.26 | 0.09 | 0.26 | 0.02 | 0.01 | 0.12 | –0.10 | –0.22 | 0.27 | 0.12 | –0.17 | 0.43 | –0.30 | –0.10 |
| July | –0.35 | –0.13 | –0.21 | –0.03 | –0.08 | –0.17 | –0.13 | –0.48 | –0.19 | 0.23 | –0.37 | 0.31 | –0.10 | 0.10 |
| Aug. | –0.27 | –0.09 | –0.13 | 0.03 | –0.01 | 0.13 | –0.12 | 0.02 | 0.02 | 0.32 | –0.13 | 0.57 | 0.10 | 0.30 |
| Sept. | –0.05 | –0.37 | –0.18 | 0.24 | 0.10 | 0.01 | –0.28 | –0.55 | –0.34 | 0.23 | –0.09 | –0.04 | 0.30 | 0.50 |
| Oct. | –0.11 | –0.53 | –0.16 | –0.03 | –0.04 | –0.03 | –0.14 | –0.55 | –0.09 | –0.04 | –0.02 | 0.02 | 0.50 | 0.80 |
| Nov. | 0.12 | –0.34 | –0.09 | –0.15 | –0.14 | –0.12 | 0.20 | –0.30 | 0.07 | –0.19 | –0.18 | –0.23 | > | 0.80 |
| Dec. | 0.70 | 0.15 | 0.34 | 0.10 | 0.03 | 0.19 | 0.63 | 0.16 | 0.15 | 0.12 | 0.14 | 0.23 | | |

**Table 4.5.** Summary of results for Region 4–Alabama/Western Georgia, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

| Month | Average temperature | | | | | | Temperature variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | –0.80 | –0.69 | –0.90 | 0.09 | 0.04 | –0.06 | –0.06 | –0.09 | –0.16 | –0.17 | –0.18 | –0.13 | < | –0.80 |
| Feb. | –0.58 | –0.54 | –0.72 | 0.02 | –0.00 | 0.02 | 0.56 | 0.39 | 0.22 | 0.24 | 0.13 | 0.23 | –0.80 | –0.50 |
| Mar. | –0.35 | –0.40 | –0.48 | –0.01 | –0.05 | –0.07 | 0.21 | 0.11 | 0.05 | 0.17 | 0.11 | 0.24 | –0.50 | –0.30 |
| Apr. | –0.15 | –0.25 | –0.28 | –0.01 | 0.00 | –0.02 | 0.39 | 0.24 | 0.16 | 0.17 | 0.03 | 0.20 | –0.30 | –0.10 |
| May | –0.07 | –0.19 | –0.18 | 0.02 | 0.02 | 0.00 | 0.07 | –0.10 | –0.06 | –0.09 | –0.02 | –0.05 | –0.10 | 0.10 |
| June | –0.03 | –0.18 | –0.15 | 0.00 | 0.01 | –0.01 | 0.07 | –0.33 | –0.12 | –0.06 | 0.04 | 0.02 | 0.10 | 0.30 |
| July | 0.02 | –0.17 | –0.09 | –0.00 | –0.00 | –0.00 | 0.98 | 0.07 | 0.75 | 0.11 | –0.01 | 0.37 | 0.30 | 0.50 |
| Aug. | 0.01 | –0.16 | –0.09 | 0.01 | –0.00 | 0.01 | 0.86 | –0.03 | 0.46 | 0.20 | 0.08 | 0.40 | 0.50 | 0.80 |
| Sept. | –0.06 | –0.19 | –0.16 | 0.01 | –0.01 | –0.02 | 0.39 | –0.08 | 0.05 | 0.05 | 0.03 | 0.30 | > | 0.80 |
| Oct. | –0.13 | –0.21 | –0.18 | 0.01 | –0.01 | –0.00 | 0.26 | 0.04 | 0.06 | 0.01 | –0.04 | 0.21 | | |
| Nov. | –0.28 | –0.28 | –0.37 | –0.02 | –0.05 | –0.00 | 0.16 | –0.02 | –0.19 | –0.11 | –0.02 | –0.04 | | |
| Dec. | –0.67 | –0.54 | –0.77 | –0.04 | –0.05 | –0.10 | 0.23 | –0.06 | –0.12 | –0.03 | 0.04 | 0.04 | | |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | –0.02 | –0.06 | –0.12 | –0.12 | 0.00 | –0.07 | 0.19 | 0.02 | 0.04 | 0.25 | 0.02 | 0.03 | | |
| Feb. | –0.04 | –0.16 | –0.04 | 0.02 | 0.06 | 0.14 | –0.07 | –0.23 | –0.14 | 0.26 | 0.05 | 0.11 | | |
| Mar. | 0.22 | –0.09 | –0.23 | 0.04 | 0.07 | 0.03 | 0.12 | –0.24 | –0.39 | 0.08 | –0.20 | –0.10 | < | –0.80 |
| Apr. | 0.75 | 0.31 | 0.21 | 0.06 | 0.07 | 0.13 | 0.48 | –0.04 | –0.17 | –0.05 | –0.25 | –0.24 | –0.80 | –0.50 |
| May | 0.68 | 0.12 | 0.10 | –0.07 | –0.09 | –0.14 | 0.39 | –0.19 | –0.01 | 0.21 | –0.19 | 0.01 | –0.50 | –0.30 |
| June | 0.82 | 0.28 | 0.24 | –0.03 | 0.03 | 0.27 | 0.44 | –0.18 | 0.10 | –0.00 | –0.23 | 0.42 | –0.30 | –0.10 |
| July | 0.43 | 0.13 | 0.06 | –0.04 | –0.02 | –0.13 | 0.37 | –0.35 | 0.12 | 0.23 | –0.22 | 0.34 | –0.10 | 0.10 |
| Aug. | 0.58 | 0.05 | –0.10 | –0.04 | 0.01 | 0.12 | 0.90 | –0.23 | 0.19 | 0.55 | –0.05 | 1.03 | 0.10 | 0.30 |
| Sept. | 0.09 | –0.43 | –0.37 | 0.11 | –0.01 | –0.09 | 0.03 | –0.56 | –0.27 | 0.57 | –0.13 | 0.09 | 0.30 | 0.50 |
| Oct. | 0.00 | –0.45 | –0.26 | –0.07 | –0.11 | –0.06 | 0.22 | –0.44 | –0.30 | 0.14 | –0.05 | 0.20 | 0.50 | 0.80 |
| Nov. | 0.26 | –0.12 | 0.09 | –0.18 | –0.12 | –0.00 | 0.67 | –0.03 | 0.34 | –0.15 | –0.23 | –0.07 | > | 0.80 |
| Dec. | 0.39 | 0.14 | 0.22 | 0.08 | 0.02 | 0.10 | 0.29 | –0.02 | –0.03 | 0.11 | 0.13 | –0.01 | | |

**Table 4.6.** Summary of results for Region 5–South Carolina, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

| Month | Average temperature | | | | | | Temperature variability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP |
| Jan. | –0.55 | –0.65 | –0.73 | 0.05 | 0.02 | –0.06 | 0.31 | –0.06 | –0.12 | –0.24 | –0.19 | –0.19 |
| Feb. | –0.43 | –0.53 | –0.59 | 0.00 | –0.01 | 0.01 | 0.76 | 0.33 | 0.19 | 0.11 | 0.04 | 0.17 |
| Mar. | –0.29 | –0.39 | –0.41 | –0.01 | –0.04 | –0.05 | 0.46 | 0.16 | 0.10 | 0.19 | 0.11 | 0.33 |
| Apr. | –0.16 | –0.27 | –0.27 | –0.01 | 0.00 | –0.03 | 0.49 | 0.38 | 0.19 | 0.21 | –0.05 | 0.27 |
| May | –0.10 | –0.21 | –0.20 | 0.01 | 0.02 | –0.00 | 0.06 | –0.02 | 0.03 | –0.06 | –0.01 | –0.13 |
| June. | –0.03 | –0.18 | –0.16 | 0.00 | 0.00 | –0.00 | –0.06 | –0.46 | –0.30 | –0.16 | –0.05 | –0.07 |
| July | –0.01 | –0.17 | –0.12 | –0.01 | –0.00 | –0.01 | 0.56 | –0.28 | 0.52 | –0.03 | –0.08 | 0.29 |
| Aug. | –0.02 | –0.16 | –0.11 | 0.01 | –0.00 | 0.00 | 0.59 | –0.13 | 0.38 | 0.14 | –0.02 | 0.36 |
| Sept. | –0.06 | –0.17 | –0.15 | 0.00 | –0.01 | –0.02 | 0.55 | 0.07 | 0.31 | 0.21 | 0.03 | 0.38 |
| Oct. | –0.09 | –0.19 | –0.15 | 0.01 | –0.01 | 0.00 | 0.34 | –0.06 | –0.07 | –0.10 | –0.07 | 0.10 |
| Nov. | –0.19 | –0.27 | –0.31 | –0.01 | –0.05 | –0.01 | 0.57 | –0.05 | –0.16 | –0.22 | –0.06 | –0.13 |
| Dec. | –0.46 | –0.51 | –0.63 | –0.04 | –0.05 | –0.07 | 0.74 | 0.03 | 0.01 | –0.12 | –0.02 | –0.01 |

EXPLANATION

| From | To |
|---|---|
| < | –0.80 |
| –0.80 | –0.50 |
| –0.50 | –0.30 |
| –0.30 | –0.10 |
| –0.10 | 0.10 |
| 0.10 | 0.30 |
| 0.30 | 0.50 |
| 0.50 | 0.80 |
| > | 0.80 |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP |
| Jan. | 0.08 | 0.09 | 0.03 | –0.16 | –0.07 | –0.14 | 0.17 | 0.08 | 0.14 | –0.11 | –0.03 | –0.21 |
| Feb. | 0.06 | –0.03 | 0.22 | 0.03 | 0.07 | 0.12 | –0.04 | –0.22 | 0.05 | 0.26 | –0.18 | –0.05 |
| Mar. | 0.19 | 0.06 | 0.11 | 0.12 | 0.08 | 0.06 | 0.17 | –0.09 | –0.00 | 0.27 | –0.09 | –0.01 |
| Apr. | 0.57 | 0.35 | 0.39 | 0.09 | 0.07 | 0.17 | 0.39 | –0.02 | 0.12 | 0.12 | –0.15 | –0.02 |
| May | 0.37 | –0.02 | 0.07 | –0.05 | –0.03 | 0.00 | 0.29 | –0.23 | 0.00 | 0.12 | –0.20 | 0.28 |
| June | 0.26 | –0.09 | 0.01 | –0.08 | 0.02 | 0.10 | 0.03 | –0.40 | –0.01 | 0.04 | –0.24 | 0.32 |
| July | 0.51 | –0.03 | 0.09 | –0.02 | 0.01 | 0.03 | 0.39 | –0.42 | 0.09 | 0.53 | –0.09 | 0.42 |
| Aug. | 0.23 | –0.37 | –0.36 | –0.15 | –0.06 | –0.03 | 0.04 | –0.59 | –0.31 | 0.01 | –0.22 | –0.01 |
| Sept. | –0.03 | –0.54 | –0.57 | –0.10 | –0.11 | –0.08 | –0.36 | –0.68 | –0.64 | –0.19 | –0.38 | –0.26 |
| Oct. | –0.06 | –0.49 | –0.31 | 0.01 | –0.11 | –0.10 | –0.10 | –0.55 | –0.32 | –0.05 | –0.15 | –0.19 |
| Nov. | 0.40 | –0.04 | 0.27 | –0.18 | –0.14 | –0.06 | 0.18 | –0.15 | 0.28 | –0.14 | –0.18 | –0.28 |
| Dec. | 0.60 | 0.36 | 0.55 | –0.08 | –0.10 | 0.03 | 0.36 | 0.10 | 0.18 | –0.03 | –0.15 | –0.10 |

EXPLANATION

| From | To |
|---|---|
| < | –0.80 |
| –0.80 | –0.50 |
| –0.50 | –0.30 |
| –0.30 | –0.10 |
| –0.10 | 0.10 |
| 0.10 | 0.30 |
| 0.30 | 0.50 |
| 0.50 | 0.80 |
| > | 0.80 |

**Table 4.7.** Summary of results for Region 6–Southern Appalachians, for CLARENCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

| Month | Average temperature | | | | | | Temperature variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | –1.68 | –1.46 | –1.89 | 0.20 | –0.01 | –0.21 | –0.10 | –0.12 | –0.20 | –0.17 | –0.10 | –0.11 | < | –0.80 |
| Feb. | –1.05 | –1.04 | –1.26 | 0.00 | –0.09 | –0.02 | 0.47 | 0.33 | 0.07 | 0.16 | 0.08 | 0.18 | –0.80 | –0.50 |
| Mar. | –0.53 | –0.62 | –0.67 | –0.03 | –0.10 | –0.13 | 0.20 | 0.21 | 0.05 | 0.19 | 0.12 | 0.30 | –0.50 | –0.30 |
| Apr. | –0.23 | –0.35 | –0.36 | –0.02 | –0.02 | –0.06 | 0.33 | 0.28 | 0.15 | 0.13 | –0.00 | 0.12 | –0.30 | –0.10 |
| May | –0.12 | –0.23 | –0.22 | 0.01 | 0.01 | –0.01 | –0.01 | –0.04 | –0.07 | –0.09 | 0.00 | –0.07 | –0.10 | 0.10 |
| June | –0.06 | –0.18 | –0.16 | 0.00 | –0.01 | –0.02 | –0.06 | –0.19 | –0.23 | –0.08 | –0.01 | –0.02 | 0.10 | 0.30 |
| July | –0.04 | –0.16 | –0.11 | –0.01 | –0.02 | –0.02 | 0.13 | –0.21 | –0.06 | –0.03 | –0.06 | 0.04 | 0.30 | 0.50 |
| Aug. | –0.05 | –0.15 | –0.12 | 0.01 | –0.01 | –0.01 | 0.22 | –0.11 | –0.05 | 0.03 | –0.02 | 0.10 | 0.50 | 0.80 |
| Sept. | –0.12 | –0.20 | –0.20 | 0.01 | –0.02 | –0.03 | 0.08 | –0.05 | –0.02 | 0.05 | 0.01 | 0.13 | > | 0.80 |
| Oct. | –0.21 | –0.25 | –0.23 | 0.02 | –0.03 | –0.02 | 0.08 | –0.02 | –0.12 | –0.06 | –0.00 | 0.12 | | |
| Nov. | –0.42 | –0.40 | –0.48 | –0.01 | –0.10 | –0.02 | 0.11 | –0.05 | –0.23 | –0.08 | 0.02 | –0.06 | | |
| Dec. | –1.19 | –0.94 | –1.29 | –0.08 | –0.15 | –0.21 | 0.25 | 0.03 | –0.07 | –0.01 | 0.04 | 0.12 | | |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | –0.17 | –0.02 | –0.04 | –0.08 | 0.01 | –0.08 | –0.14 | –0.14 | –0.11 | 0.15 | 0.01 | 0.02 | | |
| Feb. | –0.09 | 0.05 | 0.04 | 0.03 | 0.10 | 0.09 | –0.05 | –0.06 | –0.15 | 0.15 | –0.05 | –0.06 | | |
| Mar. | 0.03 | 0.02 | –0.08 | 0.06 | 0.07 | –0.03 | 0.01 | –0.22 | –0.25 | –0.10 | –0.21 | –0.29 | < | –0.80 |
| Apr. | 0.67 | 0.29 | 0.21 | 0.04 | 0.06 | 0.21 | 0.56 | 0.14 | –0.14 | 0.13 | –0.24 | –0.14 | –0.80 | –0.50 |
| May | 0.55 | –0.13 | –0.05 | –0.02 | –0.05 | –0.08 | 0.41 | –0.35 | –0.14 | 0.10 | –0.31 | –0.11 | –0.50 | –0.30 |
| June | 1.13 | –0.06 | 0.09 | –0.03 | 0.06 | 0.18 | 0.70 | –0.42 | –0.02 | 0.11 | –0.12 | 0.42 | –0.30 | –0.10 |
| July | 1.11 | –0.08 | 0.04 | 0.02 | 0.06 | 0.03 | 0.88 | –0.35 | 0.19 | 0.06 | –0.14 | 0.28 | –0.10 | 0.10 |
| Aug. | 0.92 | –0.29 | –0.20 | –0.04 | 0.05 | 0.05 | 0.87 | –0.44 | –0.16 | 0.24 | –0.05 | 0.20 | 0.10 | 0.30 |
| Sept. | 0.23 | –0.45 | –0.49 | 0.03 | –0.08 | –0.00 | 0.05 | –0.57 | –0.48 | 0.22 | –0.13 | 0.13 | 0.30 | 0.50 |
| Oct. | 0.00 | –0.31 | –0.25 | –0.06 | –0.20 | –0.15 | 0.06 | –0.31 | –0.36 | 0.13 | –0.20 | –0.05 | 0.50 | 0.80 |
| Nov. | 0.27 | 0.14 | 0.24 | –0.12 | –0.06 | 0.04 | 0.71 | 0.22 | 0.15 | –0.04 | –0.09 | –0.08 | > | 0.80 |
| Dec. | 0.11 | 0.21 | 0.29 | –0.03 | –0.03 | 0.02 | –0.08 | –0.16 | –0.22 | –0.00 | 0.03 | –0.15 | | |

**Table 4.8.** Summary of results for Region 7– Eastern North Carolina, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

| Month | Average temperature | | | | | | Temperature variability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP |
| Jan. | –0.77 | –0.79 | –0.91 | 0.04 | –0.00 | –0.11 | 0.22 | 0.04 | 0.00 | –0.25 | –0.12 | –0.18 |
| Feb. | –0.55 | –0.64 | –0.69 | –0.03 | –0.04 | 0.01 | 0.56 | 0.36 | 0.19 | –0.03 | –0.07 | 0.10 |
| Mar. | –0.34 | –0.43 | –0.44 | –0.03 | –0.05 | –0.06 | 0.54 | 0.44 | 0.25 | 0.32 | 0.15 | 0.52 |
| Apr. | –0.19 | –0.30 | –0.29 | –0.02 | –0.01 | –0.05 | 0.64 | 0.66 | 0.36 | 0.25 | –0.05 | 0.31 |
| May | –0.11 | –0.21 | –0.19 | 0.01 | 0.02 | –0.00 | 0.21 | 0.18 | 0.27 | –0.01 | 0.05 | –0.07 |
| June | –0.05 | –0.15 | –0.15 | –0.00 | –0.01 | –0.00 | 0.07 | –0.30 | –0.16 | –0.10 | –0.00 | 0.04 |
| July | –0.04 | –0.14 | –0.12 | –0.01 | –0.01 | –0.01 | 0.39 | –0.23 | 0.24 | –0.08 | –0.08 | 0.18 |
| Aug. | –0.04 | –0.14 | –0.12 | 0.00 | –0.01 | 0.00 | 0.59 | –0.09 | 0.19 | –0.01 | –0.08 | 0.16 |
| Sept. | –0.09 | –0.16 | –0.17 | –0.00 | –0.02 | –0.03 | 0.33 | 0.02 | 0.17 | 0.07 | –0.03 | 0.17 |
| Oct. | –0.13 | –0.18 | –0.16 | 0.01 | –0.02 | –0.01 | 0.24 | –0.03 | –0.05 | –0.16 | –0.08 | –0.00 |
| Nov. | –0.25 | –0.29 | –0.32 | –0.02 | –0.07 | –0.02 | 0.41 | 0.03 | –0.04 | –0.22 | –0.10 | –0.18 |
| Dec. | –0.63 | –0.58 | –0.73 | –0.07 | –0.09 | –0.11 | 0.54 | 0.12 | 0.11 | –0.15 | –0.05 | –0.02 |

| EXPLANATION | |
|---|---|
| From | To |
| < | –0.80 |
| –0.80 | –0.50 |
| –0.50 | –0.30 |
| –0.30 | –0.10 |
| –0.10 | 0.10 |
| 0.10 | 0.30 |
| 0.30 | 0.50 |
| 0.50 | 0.80 |
| > | 0.80 |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP |
| Jan. | –0.15 | 0.11 | 0.07 | –0.17 | –0.07 | –0.17 | 0.13 | 0.05 | 0.11 | –0.15 | –0.10 | –0.33 |
| Feb. | –0.07 | 0.12 | 0.32 | 0.08 | 0.11 | 0.08 | –0.07 | –0.06 | 0.13 | 0.14 | –0.24 | –0.26 |
| Mar. | –0.08 | 0.14 | 0.08 | –0.02 | –0.00 | –0.01 | 0.15 | 0.07 | 0.24 | 0.36 | –0.15 | –0.06 |
| Apr. | 0.34 | 0.27 | 0.30 | 0.13 | 0.06 | 0.16 | 0.36 | 0.10 | 0.05 | 0.14 | –0.20 | –0.06 |
| May | 0.38 | –0.13 | –0.02 | –0.04 | –0.01 | –0.03 | 0.62 | –0.22 | –0.01 | 0.03 | –0.22 | –0.02 |
| June | 0.74 | –0.11 | 0.00 | 0.06 | 0.08 | 0.20 | 0.72 | –0.42 | –0.08 | 0.34 | –0.17 | 0.27 |
| July | 0.75 | –0.21 | –0.02 | 0.04 | 0.06 | 0.08 | 0.86 | –0.36 | 0.08 | 0.13 | –0.12 | 0.02 |
| Aug. | 0.42 | –0.49 | –0.34 | –0.08 | 0.00 | –0.02 | 0.50 | –0.63 | –0.25 | 0.06 | –0.12 | –0.07 |
| Sept. | –0.06 | –0.62 | –0.61 | –0.17 | –0.16 | –0.11 | –0.27 | –0.72 | –0.72 | –0.34 | –0.42 | –0.40 |
| Oct. | 0.00 | –0.40 | –0.34 | 0.04 | –0.14 | –0.14 | 0.22 | –0.35 | –0.09 | –0.03 | –0.22 | –0.23 |
| Nov. | 0.26 | 0.21 | 0.22 | –0.09 | –0.07 | 0.01 | 0.37 | 0.22 | 0.04 | –0.07 | –0.08 | –0.12 |
| Dec. | 0.22 | 0.46 | 0.63 | –0.09 | –0.12 | 0.00 | 0.15 | 0.06 | 0.05 | –0.07 | –0.18 | –0.26 |

| EXPLANATION | |
|---|---|
| From | To |
| < | –0.80 |
| –0.80 | –0.50 |
| –0.50 | –0.30 |
| –0.30 | –0.10 |
| –0.10 | 0.10 |
| 0.10 | 0.30 |
| 0.30 | 0.50 |
| 0.50 | 0.80 |
| > | 0.80 |

**Table 4.9.** Summary of results for Region 8—Louisiana/Mississippi Coast, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

[NA, not applicable]

| Month | Average temperature | | | | | | Temperature variability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP |
| Jan. | NA | –0.40 | –0.61 | 0.07 | 0.05 | –0.02 | NA | 0.17 | –0.00 | –0.02 | –0.12 | –0.06 |
| Feb. | NA | –0.31 | –0.51 | 0.01 | 0.01 | 0.03 | NA | 0.52 | 0.38 | 0.25 | 0.21 | 0.27 |
| Mar. | NA | –0.27 | –0.38 | 0.00 | –0.02 | –0.04 | NA | 0.33 | 0.21 | 0.29 | 0.19 | 0.29 |
| Apr. | NA | –0.18 | –0.25 | 0.00 | 0.01 | –0.00 | NA | 0.14 | –0.01 | 0.14 | 0.11 | 0.14 |
| May | NA | –0.17 | –0.19 | 0.01 | 0.01 | 0.00 | NA | –0.03 | –0.11 | 0.10 | 0.02 | 0.19 |
| June | NA | –0.16 | –0.16 | 0.00 | 0.01 | –0.01 | NA | 0.49 | –0.02 | 0.12 | 0.01 | 0.12 |
| July | NA | –0.12 | –0.08 | 0.00 | 0.01 | 0.01 | NA | 1.37 | 1.62 | 0.07 | –0.01 | 0.44 |
| Aug. | NA | –0.13 | –0.07 | 0.01 | 0.01 | 0.01 | NA | 0.72 | 1.11 | 0.10 | 0.09 | 0.37 |
| Sept. | NA | –0.17 | –0.15 | 0.01 | –0.00 | –0.01 | NA | 0.19 | 0.18 | 0.08 | 0.00 | 0.31 |
| Oct. | NA | –0.17 | –0.18 | 0.01 | –0.01 | –0.00 | NA | 0.23 | 0.16 | 0.08 | –0.06 | 0.20 |
| Nov. | NA | –0.21 | –0.34 | 0.00 | –0.03 | 0.00 | NA | 0.18 | –0.06 | –0.11 | –0.01 | –0.05 |
| Dec. | NA | –0.36 | –0.59 | –0.02 | –0.02 | –0.06 | NA | 0.22 | 0.09 | –0.04 | 0.05 | 0.09 |

| EXPLANATION | |
|---|---|
| From | To |
| < | –0.80 |
| –0.80 | –0.50 |
| –0.50 | –0.30 |
| –0.30 | –0.10 |
| –0.10 | 0.10 |
| 0.10 | 0.30 |
| 0.30 | 0.50 |
| 0.50 | 0.80 |
| > | 0.80 |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP |
| Jan. | NA | –0.31 | –0.34 | –0.22 | –0.07 | –0.12 | NA | –0.35 | –0.51 | –0.25 | –0.11 | –0.15 |
| Feb. | NA | –0.20 | –0.22 | –0.01 | –0.00 | 0.05 | NA | –0.29 | –0.37 | –0.09 | –0.06 | –0.07 |
| Mar. | NA | 0.00 | –0.17 | –0.08 | –0.04 | –0.01 | NA | –0.12 | –0.27 | 0.08 | –0.02 | 0.15 |
| Apr. | NA | 0.45 | 0.23 | –0.06 | –0.00 | 0.06 | NA | –0.23 | –0.32 | –0.07 | –0.20 | –0.32 |
| May | NA | 0.28 | 0.13 | –0.13 | –0.16 | –0.17 | NA | –0.13 | –0.04 | 0.13 | –0.21 | –0.01 |
| June | NA | 0.21 | 0.24 | –0.09 | –0.06 | 0.05 | NA | 0.09 | 0.38 | –0.01 | –0.23 | 0.11 |
| July | NA | –0.18 | –0.29 | –0.04 | –0.08 | –0.36 | NA | 0.11 | 0.19 | 0.34 | –0.23 | 0.14 |
| Aug. | NA | –0.09 | –0.14 | –0.02 | –0.05 | –0.03 | NA | –0.02 | 0.20 | 0.20 | –0.16 | 0.37 |
| Sept. | NA | –0.31 | –0.04 | 0.04 | –0.04 | –0.08 | NA | –0.09 | 0.17 | 0.14 | –0.17 | 0.04 |
| Oct. | NA | –0.44 | –0.42 | –0.10 | –0.10 | –0.13 | NA | –0.35 | –0.27 | 0.07 | –0.10 | –0.04 |
| Nov. | NA | –0.28 | –0.24 | –0.21 | –0.14 | 0.01 | NA | –0.01 | –0.08 | 0.00 | –0.16 | –0.00 |
| Dec. | NA | –0.13 | –0.14 | –0.06 | –0.04 | 0.03 | NA | –0.11 | –0.17 | 0.20 | –0.07 | 0.18 |

| EXPLANATION | |
|---|---|
| From | To |
| < | –0.80 |
| –0.80 | –0.50 |
| –0.50 | –0.30 |
| –0.30 | –0.10 |
| –0.10 | 0.10 |
| 0.10 | 0.30 |
| 0.30 | 0.50 |
| 0.50 | 0.80 |
| > | 0.80 |

**Table 4.10.** Summary of results for Region 9–Northern Mississippi/Northern Louisiana/Southern Arkansas, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

[NA, not applicable]

| Month | Average temperature | | | | | | Temperature variability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP |
| Jan. | NA | –0.65 | –0.96 | 0.16 | 0.08 | –0.01 | NA | –0.07 | –0.06 | 0.00 | –0.17 | 0.01 |
| Feb. | NA | –0.48 | –0.74 | 0.02 | –0.00 | 0.03 | NA | 0.29 | 0.11 | 0.16 | 0.07 | 0.22 |
| Mar. | NA | –0.35 | –0.46 | –0.01 | –0.05 | –0.07 | NA | 0.11 | 0.06 | 0.35 | 0.21 | 0.32 |
| Apr. | NA | –0.20 | –0.26 | –0.01 | 0.00 | –0.02 | NA | 0.14 | 0.09 | 0.13 | 0.03 | 0.18 |
| May | NA | –0.17 | –0.17 | 0.02 | 0.02 | 0.01 | NA | –0.17 | –0.08 | –0.02 | –0.03 | 0.05 |
| June | NA | –0.16 | –0.13 | 0.00 | 0.01 | –0.00 | NA | 0.19 | 0.29 | 0.10 | 0.10 | 0.18 |
| July | NA | –0.11 | –0.04 | 0.00 | 0.01 | 0.00 | NA | 1.11 | 1.64 | 0.16 | 0.08 | 0.46 |
| Aug. | NA | –0.13 | –0.04 | 0.01 | 0.01 | 0.02 | NA | 0.50 | 1.01 | 0.18 | 0.11 | 0.42 |
| Sept. | NA | –0.17 | –0.13 | 0.01 | –0.00 | –0.01 | NA | –0.12 | 0.15 | 0.00 | –0.04 | 0.28 |
| Oct. | NA | –0.18 | –0.17 | 0.02 | –0.00 | 0.00 | NA | 0.19 | 0.34 | 0.08 | –0.04 | 0.29 |
| Nov. | NA | –0.27 | –0.40 | 0.01 | –0.03 | 0.01 | NA | –0.05 | –0.24 | –0.09 | –0.06 | –0.00 |
| Dec. | NA | –0.52 | –0.83 | –0.02 | –0.04 | –0.10 | NA | –0.05 | –0.19 | 0.06 | 0.10 | 0.20 |

| EXPLANATION | |
|---|---|
| From | To |
| < | –0.80 |
| –0.80 | –0.50 |
| –0.50 | –0.30 |
| –0.30 | –0.10 |
| –0.10 | 0.10 |
| 0.10 | 0.30 |
| 0.30 | 0.50 |
| 0.50 | 0.80 |
| > | 0.80 |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP |
| Jan. | NA | –0.26 | –0.31 | –0.11 | –0.03 | –0.14 | NA | –0.34 | –0.46 | 0.02 | –0.08 | –0.15 |
| Feb. | NA | –0.16 | –0.22 | 0.00 | –0.02 | 0.05 | NA | –0.17 | –0.34 | –0.03 | –0.09 | –0.06 |
| Mar. | NA | –0.09 | –0.30 | –0.05 | –0.01 | –0.01 | NA | –0.20 | –0.40 | –0.11 | –0.22 | –0.08 |
| Apr. | NA | 0.42 | 0.07 | 0.04 | –0.01 | –0.00 | NA | –0.25 | –0.39 | –0.21 | –0.27 | –0.44 |
| May | NA | 0.62 | 0.15 | –0.06 | –0.11 | –0.10 | NA | 0.33 | 0.00 | 0.17 | –0.14 | 0.08 |
| June | NA | 0.73 | 0.26 | –0.15 | –0.11 | 0.07 | NA | 0.36 | 0.38 | –0.03 | –0.27 | 0.22 |
| July | NA | 0.19 | –0.08 | –0.04 | –0.03 | –0.30 | NA | 0.25 | 0.33 | 0.17 | –0.22 | 0.17 |
| Aug. | NA | 0.47 | –0.04 | –0.01 | –0.03 | –0.01 | NA | 0.22 | 0.19 | 0.33 | –0.19 | 0.68 |
| Sept. | NA | –0.21 | –0.22 | –0.04 | 0.02 | –0.05 | NA | –0.05 | 0.16 | 0.41 | 0.04 | 0.45 |
| Oct. | NA | –0.41 | –0.49 | –0.19 | –0.21 | –0.22 | NA | –0.29 | –0.41 | 0.13 | –0.20 | –0.08 |
| Nov. | NA | –0.18 | –0.21 | –0.15 | –0.07 | 0.09 | NA | 0.16 | –0.23 | 0.15 | 0.01 | 0.28 |
| Dec. | NA | –0.29 | –0.24 | –0.07 | –0.15 | –0.07 | NA | –0.34 | –0.36 | –0.05 | –0.21 | –0.21 |

| EXPLANATION | |
|---|---|
| From | To |
| < | –0.80 |
| –0.80 | –0.50 |
| –0.50 | –0.30 |
| –0.30 | –0.10 |
| –0.10 | 0.10 |
| 0.10 | 0.30 |
| 0.30 | 0.50 |
| 0.50 | 0.80 |
| > | 0.80 |

**Table 4.11.** Summary of results for Region 10–Southeast Virginia, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

[NA, not applicable]

| Month | Average temperature | | | | | | Temperature variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | NA | –1.72 | –1.93 | 0.11 | 0.03 | –0.21 | NA | 0.09 | –0.05 | –0.18 | –0.02 | –0.11 | < | –0.80 |
| Feb. | NA | –1.23 | –1.23 | –0.05 | –0.08 | 0.01 | NA | 0.44 | 0.14 | 0.04 | –0.04 | 0.13 | –0.80 | –0.50 |
| Mar. | NA | –0.64 | –0.61 | –0.05 | –0.08 | –0.11 | NA | 0.71 | 0.41 | 0.50 | 0.26 | 0.68 | –0.50 | –0.30 |
| Apr. | NA | –0.39 | –0.35 | –0.03 | –0.02 | –0.07 | NA | 1.02 | 0.63 | 0.38 | 0.09 | 0.36 | –0.30 | –0.10 |
| May | NA | –0.24 | –0.22 | 0.01 | 0.01 | –0.01 | NA | 0.40 | 0.48 | 0.06 | 0.18 | 0.09 | –0.10 | 0.10 |
| June | NA | –0.17 | –0.17 | –0.01 | –0.02 | –0.02 | NA | 0.18 | 0.15 | 0.01 | 0.15 | 0.23 | 0.10 | 0.30 |
| July | NA | –0.14 | –0.15 | –0.01 | –0.02 | –0.02 | NA | 0.15 | 0.26 | 0.08 | 0.16 | 0.24 | 0.30 | 0.50 |
| Aug. | NA | –0.16 | –0.16 | –0.00 | –0.02 | –0.01 | NA | 0.21 | 0.23 | 0.09 | 0.13 | 0.20 | 0.50 | 0.80 |
| Sept. | NA | –0.20 | –0.22 | –0.01 | –0.02 | –0.03 | NA | 0.27 | 0.27 | 0.11 | 0.16 | 0.24 | > | 0.80 |
| Oct. | NA | –0.24 | –0.23 | 0.01 | –0.02 | –0.01 | NA | 0.15 | 0.01 | –0.08 | 0.01 | 0.06 | | |
| Nov. | NA | –0.40 | –0.42 | –0.02 | –0.08 | –0.01 | NA | 0.16 | –0.05 | –0.07 | 0.02 | –0.06 | | |
| Dec. | NA | –0.99 | –1.20 | –0.08 | –0.13 | –0.18 | NA | 0.25 | 0.04 | –0.07 | 0.04 | 0.09 | | |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | NA | 0.17 | 0.28 | –0.14 | –0.04 | –0.13 | NA | –0.01 | 0.06 | –0.10 | –0.11 | –0.31 | | |
| Feb. | NA | 0.30 | 0.41 | –0.01 | 0.09 | 0.04 | NA | 0.10 | 0.13 | –0.05 | –0.28 | –0.26 | | |
| Mar. | NA | 0.26 | 0.21 | –0.01 | 0.01 | –0.05 | NA | 0.01 | 0.14 | –0.00 | –0.22 | –0.25 | < | –0.80 |
| Apr. | NA | 0.38 | 0.28 | 0.10 | –0.00 | 0.13 | NA | 0.20 | 0.10 | –0.09 | –0.15 | –0.13 | –0.80 | –0.50 |
| May | NA | –0.10 | 0.07 | –0.05 | –0.05 | –0.10 | NA | –0.16 | 0.11 | 0.01 | –0.22 | –0.14 | –0.50 | –0.30 |
| June | NA | –0.01 | 0.20 | –0.02 | 0.04 | 0.16 | NA | –0.49 | –0.03 | 0.05 | –0.20 | 0.27 | –0.30 | –0.10 |
| July | NA | –0.25 | –0.07 | 0.05 | 0.01 | 0.03 | NA | –0.33 | 0.06 | 0.25 | –0.21 | –0.02 | –0.10 | 0.10 |
| Aug. | NA | –0.35 | –0.17 | –0.03 | 0.08 | 0.07 | NA | –0.46 | –0.09 | 0.08 | –0.08 | –0.17 | 0.10 | 0.30 |
| Sept. | NA | –0.49 | –0.49 | –0.21 | –0.16 | –0.12 | NA | –0.62 | –0.63 | –0.37 | –0.36 | –0.36 | 0.30 | 0.50 |
| Oct. | NA | –0.30 | –0.21 | –0.04 | –0.17 | –0.18 | NA | –0.31 | –0.13 | –0.06 | –0.34 | –0.28 | 0.50 | 0.80 |
| Nov. | NA | 0.48 | 0.48 | –0.06 | –0.07 | 0.11 | NA | 0.46 | 0.01 | –0.17 | –0.18 | –0.20 | > | 0.80 |
| Dec. | NA | 0.59 | 0.79 | –0.06 | –0.10 | –0.02 | NA | –0.01 | 0.11 | –0.14 | –0.15 | –0.33 | | |

**Table 4.12.** Summary of results for Region 11–Western Virginia/Eastern Kentucky, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

[NA, not applicable]

| Month | Average temperature | | | | | | Temperature variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | NA | –6.05 | –7.73 | 1.26 | 0.55 | –0.38 | NA | –0.17 | –0.28 | –0.19 | –0.13 | –0.15 | < | –0.80 |
| Feb. | NA | –1.91 | –2.17 | 0.04 | –0.02 | 0.16 | NA | 0.28 | –0.10 | 0.09 | –0.04 | 0.16 | –0.80 | –0.50 |
| Mar. | NA | –0.78 | –0.80 | –0.01 | –0.08 | –0.13 | NA | 0.26 | –0.00 | 0.36 | 0.11 | 0.43 | –0.50 | –0.30 |
| Apr. | NA | –0.38 | –0.37 | –0.01 | 0.02 | –0.03 | NA | 0.63 | 0.43 | 0.23 | –0.02 | 0.18 | –0.30 | –0.10 |
| May | NA | –0.22 | –0.20 | 0.03 | 0.05 | 0.03 | NA | 0.10 | 0.10 | –0.15 | 0.01 | –0.07 | –0.10 | 0.10 |
| June | NA | –0.16 | –0.14 | 0.01 | 0.02 | 0.01 | NA | 0.01 | 0.10 | –0.07 | 0.09 | 0.03 | 0.10 | 0.30 |
| July | NA | –0.13 | –0.10 | 0.00 | 0.01 | –0.00 | NA | 0.03 | 0.34 | –0.02 | 0.02 | 0.09 | 0.30 | 0.50 |
| Aug. | NA | –0.14 | –0.11 | 0.02 | 0.01 | 0.03 | NA | 0.11 | 0.19 | –0.04 | –0.06 | 0.15 | 0.50 | 0.80 |
| Sept. | NA | –0.20 | –0.19 | 0.02 | 0.01 | 0.00 | NA | 0.03 | 0.07 | 0.01 | –0.03 | 0.10 | > | 0.80 |
| Oct. | NA | –0.26 | –0.22 | 0.05 | 0.02 | 0.03 | NA | –0.01 | –0.17 | –0.09 | –0.07 | 0.05 | | |
| Nov. | NA | –0.45 | –0.52 | 0.00 | –0.06 | 0.04 | NA | –0.07 | –0.31 | –0.08 | –0.07 | –0.13 | | |
| Dec. | NA | –1.50 | –2.05 | –0.07 | –0.11 | –0.26 | NA | –0.01 | –0.21 | 0.04 | 0.02 | 0.16 | | |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | NA | 0.06 | 0.13 | 0.04 | 0.11 | –0.01 | NA | –0.26 | –0.06 | 0.18 | 0.19 | –0.04 | | |
| Feb. | NA | 0.22 | 0.15 | 0.05 | 0.12 | 0.07 | NA | 0.09 | –0.12 | 0.21 | 0.13 | –0.03 | | |
| Mar. | NA | 0.17 | 0.10 | 0.05 | 0.11 | –0.03 | NA | –0.17 | –0.21 | –0.16 | –0.11 | –0.29 | < | –0.80 |
| Apr. | NA | 0.25 | 0.22 | –0.06 | 0.00 | 0.12 | NA | –0.08 | –0.09 | –0.09 | –0.14 | –0.13 | –0.80 | –0.50 |
| May | NA | –0.13 | –0.05 | –0.07 | –0.03 | –0.08 | NA | –0.23 | –0.01 | 0.19 | –0.13 | –0.05 | –0.50 | –0.30 |
| June | NA | 0.02 | 0.17 | 0.04 | 0.01 | 0.09 | NA | –0.28 | 0.02 | 0.30 | –0.17 | 0.18 | –0.30 | –0.10 |
| July | NA | –0.11 | –0.01 | 0.16 | 0.10 | 0.11 | NA | –0.09 | 0.47 | 0.54 | 0.01 | 0.60 | –0.10 | 0.10 |
| Aug. | NA | –0.26 | –0.15 | 0.03 | –0.00 | –0.03 | NA | –0.20 | 0.11 | 0.50 | –0.05 | 0.34 | 0.10 | 0.30 |
| Sept. | NA | –0.31 | –0.29 | –0.06 | –0.05 | 0.00 | NA | –0.39 | –0.29 | 0.28 | –0.09 | 0.19 | 0.30 | 0.50 |
| Oct. | NA | –0.09 | –0.03 | –0.08 | –0.23 | –0.16 | NA | –0.07 | –0.06 | 0.06 | –0.32 | –0.06 | 0.50 | 0.80 |
| Nov. | NA | 0.43 | 0.46 | –0.04 | –0.01 | 0.09 | NA | 0.64 | –0.01 | 0.04 | –0.11 | –0.17 | > | 0.80 |
| Dec. | NA | 0.22 | 0.33 | –0.07 | –0.05 | –0.02 | NA | –0.26 | –0.32 | –0.13 | –0.13 | –0.33 | | |

**Table 4.13.** Summary of results for Region 12–Western Kentucky/Tennessee, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

[NA, not applicable]

| Month | Average temperature | | | | | | Temperature variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | NA | –1.66 | –2.41 | 0.42 | 0.21 | –0.08 | NA | –0.17 | –0.20 | –0.14 | –0.15 | –0.13 | < | –0.80 |
| Feb. | NA | –0.99 | –1.28 | 0.05 | –0.01 | 0.07 | NA | 0.22 | –0.09 | 0.09 | –0.05 | 0.10 | –0.80 | –0.50 |
| Mar. | NA | –0.54 | –0.61 | –0.01 | –0.08 | –0.12 | NA | 0.23 | 0.03 | 0.33 | 0.15 | 0.37 | –0.50 | –0.30 |
| Apr. | NA | –0.27 | –0.30 | –0.01 | 0.01 | –0.03 | NA | 0.40 | 0.33 | 0.22 | –0.02 | 0.15 | –0.30 | –0.10 |
| May | NA | –0.18 | –0.17 | 0.02 | 0.04 | 0.02 | NA | –0.09 | 0.01 | –0.13 | –0.05 | –0.09 | –0.10 | 0.10 |
| June | NA | –0.15 | –0.12 | 0.01 | 0.02 | 0.00 | NA | –0.10 | 0.30 | –0.08 | 0.06 | 0.08 | 0.10 | 0.30 |
| July | NA | –0.12 | –0.06 | 0.00 | 0.01 | –0.00 | NA | 0.23 | 0.82 | 0.08 | 0.04 | 0.38 | 0.30 | 0.50 |
| Aug. | NA | –0.13 | –0.06 | 0.02 | 0.01 | 0.02 | NA | 0.04 | 0.44 | 0.08 | –0.02 | 0.34 | 0.50 | 0.80 |
| Sept. | NA | –0.17 | –0.15 | 0.02 | 0.00 | –0.01 | NA | –0.10 | 0.06 | –0.02 | –0.06 | 0.19 | > | 0.80 |
| Oct. | NA | –0.21 | –0.19 | 0.02 | 0.01 | 0.01 | NA | 0.04 | 0.02 | –0.05 | –0.13 | 0.10 | | |
| Nov. | NA | –0.35 | –0.46 | 0.01 | –0.05 | 0.01 | NA | –0.12 | –0.31 | –0.08 | –0.08 | –0.11 | | |
| Dec. | NA | –0.88 | –1.36 | –0.08 | –0.09 | –0.20 | NA | –0.07 | –0.21 | 0.05 | 0.07 | 0.18 | | |

| Month | Average precipitation | | | | | | Precipitation variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | NA | –0.12 | –0.13 | 0.02 | 0.10 | –0.03 | NA | –0.27 | –0.24 | 0.24 | 0.21 | 0.06 | | |
| Feb. | NA | 0.02 | –0.10 | 0.03 | 0.06 | 0.08 | NA | –0.09 | –0.32 | –0.02 | 0.04 | 0.04 | | |
| Mar. | NA | –0.10 | –0.18 | –0.04 | 0.05 | –0.07 | NA | –0.30 | –0.38 | –0.21 | –0.21 | –0.33 | < | –0.80 |
| Apr. | NA | 0.25 | 0.15 | 0.02 | 0.01 | 0.17 | NA | –0.12 | –0.15 | 0.01 | –0.24 | –0.16 | –0.80 | –0.50 |
| May | NA | –0.05 | –0.02 | –0.06 | –0.04 | –0.09 | NA | –0.30 | –0.04 | 0.10 | –0.16 | 0.07 | –0.50 | –0.30 |
| June | NA | 0.24 | 0.19 | –0.04 | –0.02 | 0.09 | NA | –0.00 | 0.16 | 0.09 | –0.19 | 0.31 | –0.30 | –0.10 |
| July | NA | 0.12 | 0.03 | –0.05 | –0.00 | –0.06 | NA | –0.03 | 0.35 | 0.28 | –0.07 | 0.51 | –0.10 | 0.10 |
| Aug. | NA | 0.05 | –0.17 | –0.08 | 0.00 | –0.03 | NA | –0.14 | 0.02 | 0.36 | –0.05 | 0.74 | 0.10 | 0.30 |
| Sept. | NA | –0.39 | –0.42 | –0.05 | –0.09 | –0.09 | NA | –0.48 | –0.37 | 0.26 | –0.15 | 0.17 | 0.30 | 0.50 |
| Oct. | NA | –0.23 | –0.25 | –0.06 | –0.23 | –0.17 | NA | –0.01 | –0.10 | 0.51 | –0.25 | 0.04 | 0.50 | 0.80 |
| Nov. | NA | 0.08 | 0.05 | –0.05 | –0.03 | 0.05 | NA | 0.38 | –0.11 | 0.06 | –0.04 | –0.00 | > | 0.80 |
| Dec. | NA | –0.17 | –0.09 | –0.08 | –0.10 | –0.07 | NA | –0.33 | –0.45 | –0.13 | –0.16 | –0.37 | | |

**Table 4.14.** Summary of results for Region 13–Northern Arkansas, for CLAREnCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

[NA, not applicable]

| Month | Average temperature | | | | | | | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | NA | –1.19 | –1.93 | 0.30 | 0.17 | 0.02 | NA | –0.09 | –0.06 | –0.07 | –0.18 | –0.05 | < | –0.80 |
| Feb. | NA | –0.76 | –1.13 | 0.02 | –0.04 | 0.03 | NA | 0.14 | –0.09 | –0.00 | –0.12 | 0.06 | –0.80 | –0.50 |
| Mar. | NA | –0.46 | –0.58 | –0.04 | –0.08 | –0.11 | NA | 0.14 | 0.01 | 0.30 | 0.17 | 0.32 | –0.50 | –0.30 |
| Apr. | NA | –0.25 | –0.32 | –0.02 | –0.01 | –0.04 | NA | 0.27 | 0.23 | 0.19 | –0.00 | 0.15 | –0.30 | –0.10 |
| May | NA | –0.18 | –0.19 | 0.02 | 0.02 | 0.01 | NA | –0.17 | –0.06 | –0.07 | –0.04 | –0.03 | –0.10 | 0.10 |
| June | NA | –0.16 | –0.12 | –0.00 | 0.01 | –0.01 | NA | –0.06 | 0.31 | 0.03 | 0.15 | 0.15 | 0.10 | 0.30 |
| July | NA | –0.12 | –0.05 | –0.00 | –0.00 | –0.01 | NA | 0.44 | 0.87 | 0.07 | 0.03 | 0.34 | 0.30 | 0.50 |
| Aug. | NA | –0.14 | –0.04 | 0.01 | –0.00 | 0.02 | NA | 0.24 | 0.63 | 0.11 | 0.02 | 0.35 | 0.50 | 0.80 |
| Sept. | NA | –0.18 | –0.15 | 0.01 | –0.01 | –0.01 | NA | –0.12 | 0.18 | 0.00 | –0.01 | 0.21 | > | 0.80 |
| Oct. | NA | –0.22 | –0.22 | 0.02 | –0.00 | –0.00 | NA | 0.22 | 0.37 | 0.04 | 0.01 | 0.19 | | |
| Nov. | NA | –0.34 | –0.49 | 0.01 | –0.05 | 0.00 | NA | –0.14 | –0.24 | –0.10 | –0.06 | –0.05 | | |
| Dec. | NA | –0.74 | –1.28 | –0.05 | –0.09 | –0.17 | NA | –0.04 | –0.18 | 0.09 | 0.13 | 0.24 | | |

| Month | Average precipitation | | | | | | | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | NA | –0.16 | –0.13 | 0.00 | 0.07 | –0.09 | NA | –0.27 | –0.21 | 0.33 | 0.18 | 0.04 | | |
| Feb. | NA | 0.01 | –0.11 | 0.02 | 0.02 | 0.07 | NA | –0.11 | –0.32 | –0.05 | –0.05 | 0.01 | | |
| Mar. | NA | –0.07 | –0.27 | –0.03 | 0.00 | –0.07 | NA | –0.27 | –0.46 | –0.07 | –0.18 | –0.16 | < | –0.80 |
| Apr. | NA | 0.38 | 0.04 | 0.01 | –0.05 | 0.07 | NA | –0.11 | –0.26 | –0.24 | –0.23 | –0.29 | –0.80 | –0.50 |
| May | NA | 0.53 | 0.08 | 0.01 | –0.03 | –0.08 | NA | 0.37 | 0.02 | 0.22 | –0.03 | 0.16 | –0.50 | –0.30 |
| June | NA | 0.83 | 0.23 | –0.09 | –0.06 | –0.00 | NA | 0.60 | 0.35 | 0.15 | –0.13 | 0.36 | –0.30 | –0.10 |
| July | NA | 0.55 | 0.22 | 0.08 | 0.06 | –0.04 | NA | 0.39 | 0.46 | 0.25 | –0.13 | 0.38 | –0.10 | 0.10 |
| Aug. | NA | 0.80 | –0.10 | –0.05 | 0.04 | –0.04 | NA | 0.77 | 0.13 | 0.30 | –0.07 | 0.77 | 0.10 | 0.30 |
| Sept. | NA | –0.12 | –0.34 | –0.05 | –0.02 | –0.10 | NA | –0.08 | –0.03 | 0.19 | –0.10 | 0.10 | 0.30 | 0.50 |
| Oct. | NA | –0.24 | –0.34 | –0.06 | –0.23 | –0.15 | NA | –0.18 | –0.21 | 0.41 | –0.30 | 0.02 | 0.50 | 0.80 |
| Nov. | NA | –0.18 | –0.23 | –0.07 | –0.03 | 0.07 | NA | –0.05 | –0.44 | 0.29 | 0.00 | 0.10 | > | 0.80 |
| Dec. | NA | –0.37 | –0.30 | –0.13 | –0.20 | –0.14 | NA | –0.44 | –0.46 | –0.09 | –0.27 | –0.35 | | |

**Table 4.15.** Summary of results for Region 14–Southern Missouri, for CLARENCE10 (CL10), Hostetler (Host), NARCCAP (NAR), CCR, BCSD, and SERAP (SRP).

[NA, not applicable]

| Month | Average temperature | | | | | | Temperature variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | NA | –1.06 | –1.88 | 3.64 | 2.19 | 0.75 | NA | –0.14 | –0.14 | –0.12 | –0.16 | –0.11 | < | –0.80 |
| Feb. | NA | –1.39 | –2.05 | 0.03 | –0.04 | 0.08 | NA | 0.02 | –0.23 | –0.05 | –0.17 | 0.03 | –0.80 | –0.50 |
| Mar. | NA | –0.59 | –0.72 | –0.05 | –0.11 | –0.15 | NA | 0.17 | 0.02 | 0.36 | 0.16 | 0.39 | –0.50 | –0.30 |
| Apr. | NA | –0.29 | –0.36 | –0.04 | –0.01 | –0.05 | NA | 0.36 | 0.29 | 0.25 | –0.06 | 0.13 | –0.30 | –0.10 |
| May | NA | –0.17 | –0.20 | 0.01 | 0.03 | 0.02 | NA | –0.18 | –0.06 | –0.08 | –0.09 | –0.07 | –0.10 | 0.10 |
| June | NA | –0.15 | –0.11 | 0.00 | 0.01 | –0.00 | NA | –0.05 | 0.39 | 0.02 | 0.12 | 0.09 | 0.10 | 0.30 |
| July | NA | –0.12 | –0.05 | –0.00 | –0.00 | –0.01 | NA | 0.22 | 0.54 | 0.06 | 0.02 | 0.29 | 0.30 | 0.50 |
| Aug. | NA | –0.14 | –0.06 | 0.01 | –0.00 | 0.02 | NA | 0.13 | 0.40 | 0.08 | –0.03 | 0.32 | 0.50 | 0.80 |
| Sept. | NA | –0.18 | –0.16 | 0.02 | 0.00 | –0.00 | NA | –0.16 | 0.11 | –0.04 | –0.10 | 0.13 | > | 0.80 |
| Oct. | NA | –0.23 | –0.25 | 0.03 | 0.02 | 0.00 | NA | 0.22 | 0.32 | 0.04 | 0.02 | 0.10 | | |
| Nov. | NA | –0.39 | –0.57 | 0.03 | –0.05 | 0.02 | NA | –0.27 | –0.25 | –0.12 | –0.10 | –0.10 | | |
| Dec. | NA | –1.32 | –2.47 | –0.07 | –0.11 | –0.32 | NA | –0.11 | –0.20 | 0.07 | 0.09 | 0.21 | | |

| Month | Average precipitation | | | | | | Temperature variability | | | | | | EXPLANATION | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CL10 | Host | NAR | CCR | BCSD | SRP | CL10 | Host | NAR | CCR | BCSD | SRP | From | To |
| Jan. | NA | –0.04 | –0.03 | 0.01 | 0.02 | –0.09 | NA | –0.21 | –0.22 | 0.21 | 0.14 | –0.03 | | |
| Feb. | NA | 0.10 | –0.07 | –0.01 | –0.02 | 0.06 | NA | –0.08 | –0.38 | –0.07 | –0.11 | –0.02 | | |
| Mar. | NA | –0.05 | –0.18 | –0.02 | 0.02 | –0.08 | NA | –0.36 | –0.42 | 0.11 | –0.15 | –0.11 | < | –0.80 |
| Apr. | NA | 0.30 | 0.05 | –0.03 | –0.05 | 0.08 | NA | –0.13 | –0.17 | –0.23 | –0.17 | –0.22 | –0.80 | –0.50 |
| May | NA | 0.50 | 0.16 | 0.03 | 0.04 | –0.01 | NA | 0.30 | 0.01 | 0.14 | –0.05 | 0.14 | –0.50 | –0.30 |
| June | NA | 0.77 | 0.20 | –0.08 | 0.00 | –0.02 | NA | 0.43 | 0.37 | 0.06 | –0.07 | 0.16 | –0.30 | –0.10 |
| July | NA | 0.64 | 0.28 | 0.12 | 0.08 | 0.08 | NA | 0.43 | 0.33 | 0.28 | –0.07 | 0.33 | –0.10 | 0.10 |
| Aug. | NA | 0.64 | –0.05 | –0.07 | 0.00 | –0.12 | NA | 0.55 | 0.26 | 0.17 | –0.08 | 0.50 | 0.10 | 0.30 |
| Sept. | NA | 0.01 | –0.20 | –0.01 | –0.02 | –0.02 | NA | –0.22 | –0.04 | –0.07 | –0.23 | –0.19 | 0.30 | 0.50 |
| Oct. | NA | –0.11 | –0.22 | –0.02 | –0.18 | –0.06 | NA | 0.00 | 0.14 | 0.43 | –0.14 | 0.21 | 0.50 | 0.80 |
| Nov. | NA | –0.20 | –0.18 | –0.10 | –0.03 | –0.02 | NA | –0.13 | –0.42 | –0.06 | –0.05 | –0.17 | > | 0.80 |
| Dec. | NA | –0.26 | –0.22 | –0.16 | –0.22 | –0.16 | NA | –0.46 | –0.48 | –0.22 | –0.37 | –0.44 | | |

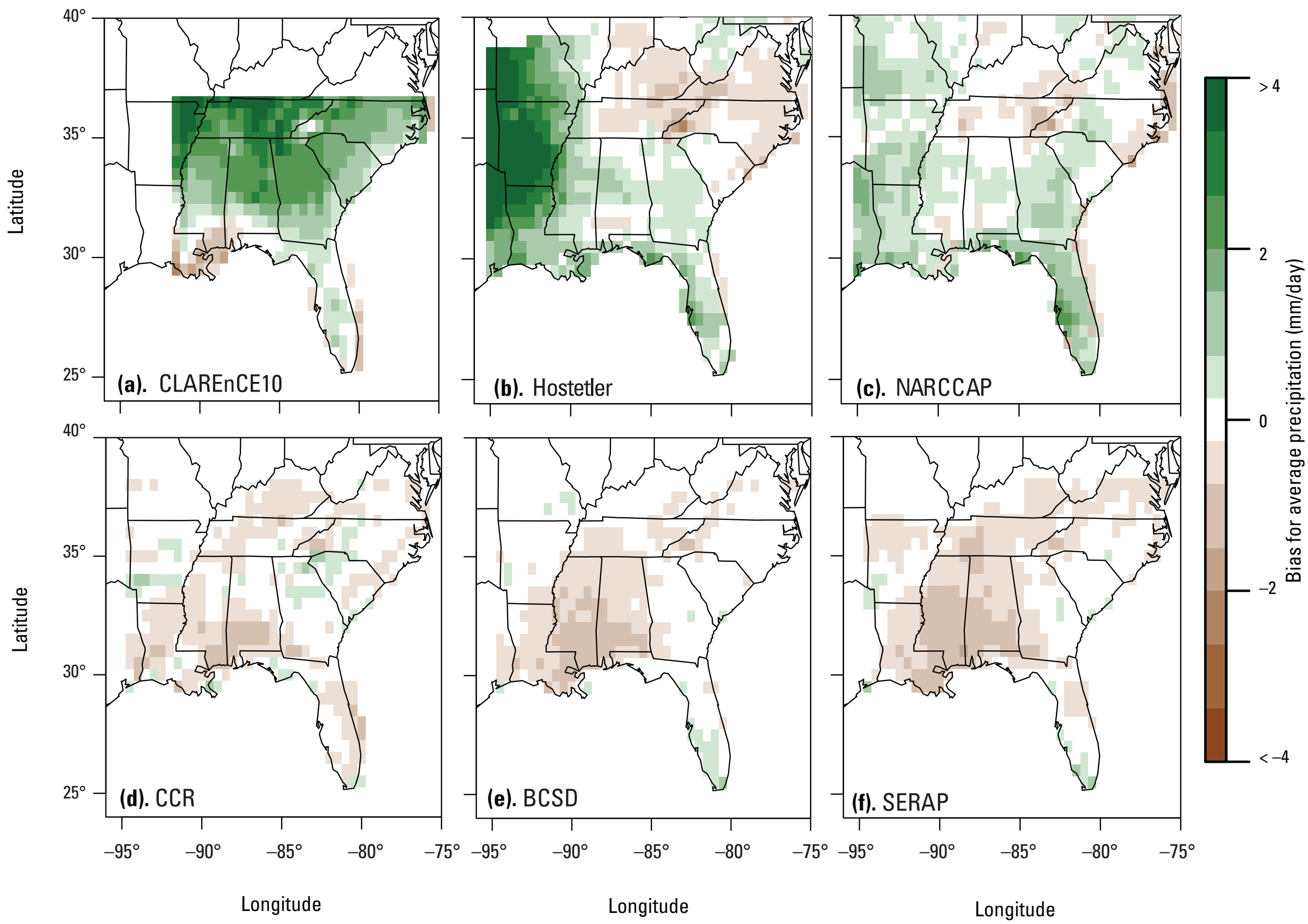


**Figure 4.3.** Bias for monthly average precipitation (mm/day) in May for (a) CLAREnCE10, (b) Hostetler, (c) NARCCAP, (d) CCR, (e) BCSD, and (f) SERAP.

The largest relative error in the statistical datasets, CCR, BCSD, and SERAP, is smaller than 1 as opposed to the larger biases seen for the dynamic datasets. Relative errors greater than 1 are in each of these datasets in January in Southern Missouri (Table 4.15) and in CCR in Western Virginia/Eastern Kentucky (Table 4.12). However, in most regions and for most months the absolute value of the relative error for each of the statistical datasets is less than 0.1 for each month.

**Temperature Variability:** Temperature variability is measured by the standard deviation of monthly temperatures; therefore, the estimated and observed values of this standard deviation are used in the calculation of relative error. The relative error in this section indicates how accurate each downscaled dataset replicates natural variability relative to PRISM. It is important to note, however, that temperature variability is also related to the frequency of hot and cold extremes. Therefore, in this instance, values of relative error less than (or greater than) zero indicate a tendency to underestimate (or overestimate) temperature variability relative to PRISM. As an example, a relative error greater than or equal to 0.5 indicates that the estimated temperature variability is 1.5 times greater than the observed temperature variability and has more frequent hot and cold extremes than historically observed relative to PRISM. The downscaled datasets tend to have a relative error within 0.3 over the entire Southeast U.S., with some exceptions. CLAREnCE10 has a relative error greater than 0.3 for most months in each of the regions it covers, indicating a tendency to overestimate temperature variability (Table 4.2–4.8). In NARCCAP, the relative error indicates a tendency to overestimate temperature variability in the summer (June, July, August) in all regions except the Southern Appalachians. In general, BCSD has relative errors within 0.1 over a large part of the Southeast U.S. and for most months. CLAREnCE10 has relative errors greater than 0.3 in most months for South Carolina (Table 4.6) and in Eastern North Carolina (Table 4.8). There are relative errors from 0.28 to 1.06 inches February through April in Southeast Virginia and Western Virginia/Eastern Kentucky in the Hostetler dataset (Tables 4.11 and 4.12)

**Average Precipitation:** CLAREnCE10 has the largest relative errors for mean precipitation in many cases for multiple months and regions in the domain. The relative error

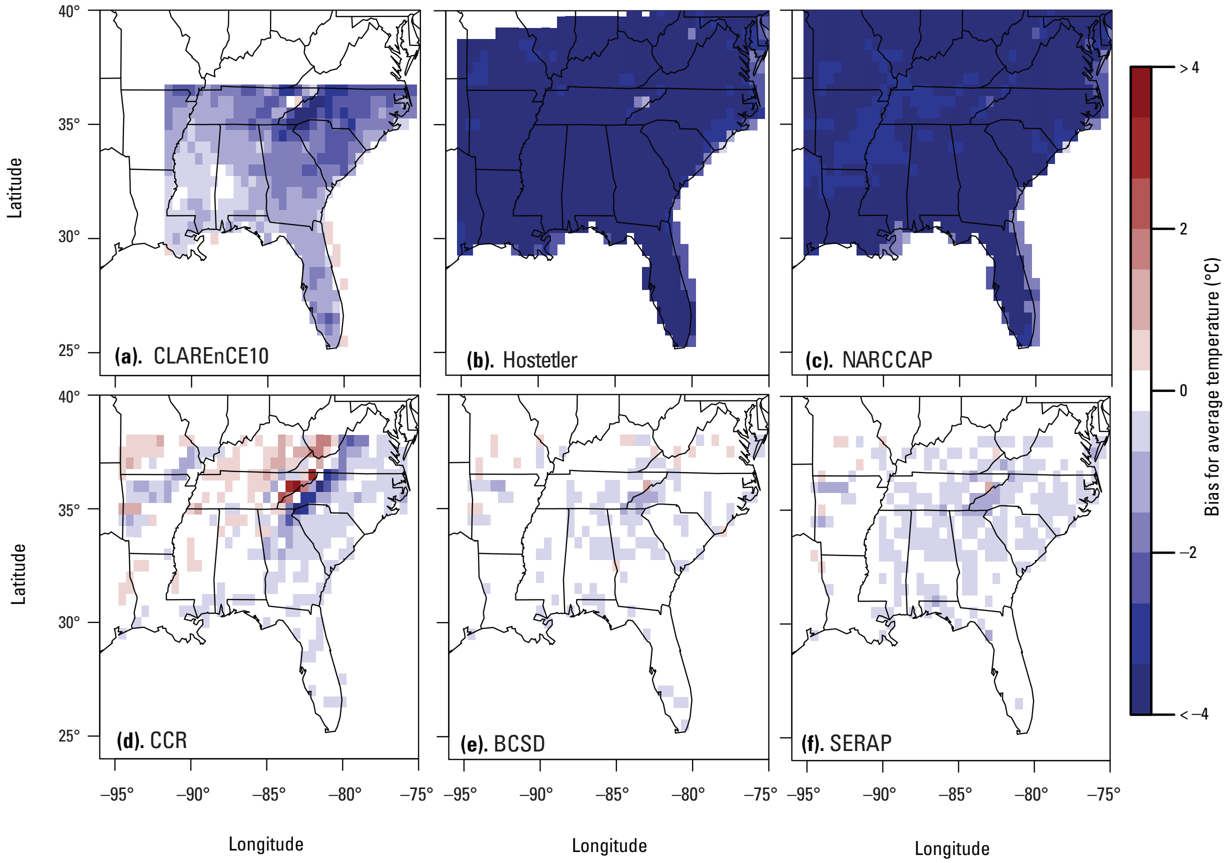


**Figure 4.4.** Bias for monthly average temperature (°C) in September for (a) CLAREnCE10, (b) Hostetler, (c) NARCCAP, (d) CCR, (e) BCSD, and (f) SERAP.

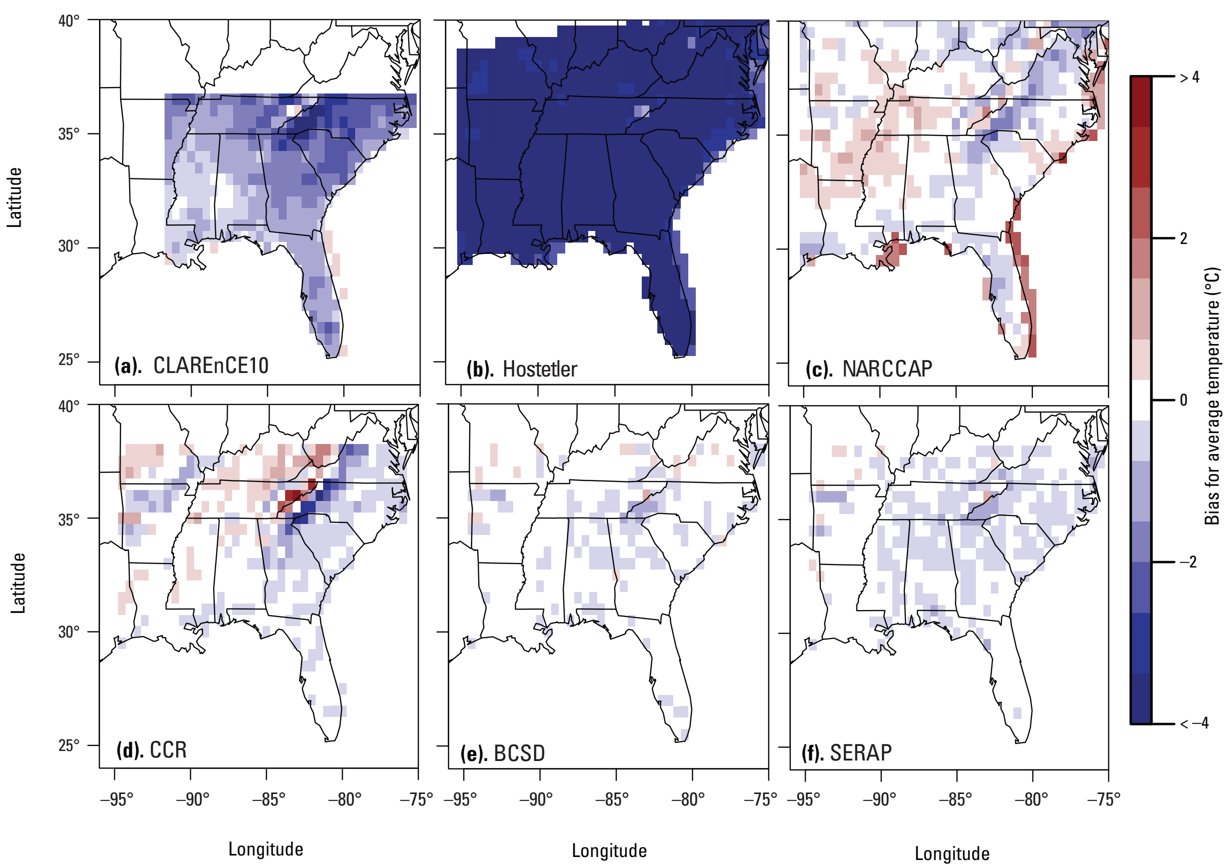


**Figure 4.5.** Bias for monthly average temperature (°C) in September for (a) CLAREnCE10, (b) Hostetler, (c) Bias Corrected NARCCAP, (d) CCR, (e) BCSD, and (f) SERAP.

also indicates a tendency to overestimate the mean precipitation, except for the summer months (June, July, and August) in Southern Florida, Northeastern Florida/Georgia Coast, and Northern Gulf Coast of Florida (Tables 4.2–4.4). The average monthly precipitation is represented well in most regions by the statistically downscaled datasets (relative errors less than 0.3 in most cases for CCR, BCSD, and SERAP), but it can also be well represented in some seasons by NARCCAP and Hostetler for some regions. NARCCAP relative errors (values from 0.22 to 0.92) show a tendency to overestimate average precipitation in Southern Florida in October–December (Table 4.2). In addition, both Hostetler and NARCCAP relative errors also show a tendency to underestimate average precipitation in several other regions in September. This is most notable for the South Carolina, Southern Appalachians, Eastern North Carolina, and Southeastern Virginia regions, where the relative errors range from –0.49 to –0.61 (Tables 4.6–4.8, 4.11). Relative errors ranging from 0.55 to 0.83 from the Hostetler dataset also indicate a tendency to overestimate average precipitation in June, July, and August in regions 13 and 14 (Tables 4.14–4.15).

**Precipitation Variability:** Precipitation variability is measured by the standard deviation of monthly precipitation; therefore, the estimated and observed values of this standard deviation are used in the calculation of relative error. The relative error in this section indicates how accurate each downscaled dataset replicates natural variability relative to PRISM. It is important, however, to note that precipitation variability is also related to the frequency of dry and wet extremes. Therefore, in this instance, values of relative error less than (or greater than) zero indicate a tendency to underestimate (or overestimate) temperature variability relative to PRISM. As an example, a relative error greater than or equal to 0.5 indicates that the estimated precipitation variability is 1.5 times larger than the observed temperature variability and has more frequent wet and dry extremes than historically observed relative to PRISM. No dataset reflects the variability of precipitation in any region throughout the entire year. In the Alabama/Western Georgia and the Southern Appalachians, the widest set of difference exists in relative errors between the downscaled datasets (Tables 4.5 and 4.7). CLAREnCE10 has the largest relative errors for precipitation variability for multiple months and regions in the Southeast U.S. The relative errors from Hostetler indicate a tendency to underestimate the variability, except in the summer in Southern Florida, Louisiana/Mississippi Coast, Northern Mississippi/Northern Louisiana/Southern Arkansas, Northern Arkansas, and Southern Missouri (Tables 4.2, 4.9, 4.10, 4.14, and 4.15). The relative errors also indicate that the variability tends to be underestimated throughout the year in all subregions by BCSD. SERAP tends to overestimate in the summer months (relative errors from 0.3 to 1.03); however, the variability is underestimated in the winter for most regions across the Southeast U.S. (relative errors from –0.35 to –0.1, Tables 4.2–4.15). CCR overestimates precipitation variability in June, July, and August for most regions across the Southeast U.S. (relative errors from 0.1 to 0.6).

### 4.2.2 Discussion

The dynamic datasets (a) CLAREnCE10, (b) Hostetler, and (c) NARCCAP have a consistent set of relative errors that indicate a cold bias for most regions. This cold bias is at least 4 ºC for most months (for example, January, Figure 4.2). It is important to note, however, that datasets analyzed in this evaluation did not receive any additional bias corrections. As mentioned in Section 2.3, there are many ways to bias correct data, and no single best bias correction technique exists. As shown in the bias maps for January temperature, the dynamic models are colder than observed temperatures by more than 4 ºC in many regions. This bias could be removed using any of the techniques described in Section 2.3. Resulting projections would be different depending on the bias removal technique used. In contrast, statistical downscaled datasets correct the cold bias from GFDL to a greater extent because they build statistical relations between the GFDL GCM and observations, so some bias correction of the GCM is built into the statistical techniques. If the dynamic datasets were bias corrected, they would similarly show less of a cold bias. BCSD does an adequate job of dampening the bias issue found in GFDL, to the point of having some areas of warm bias in January. Figure 4.3 shows the bias for monthly average precipitation (millimeters per day (mm/day)) in May for (a) CLAREnCE10, (b) Hostetler, (c) NARCCAP, (d) CCR, (e) BCSD, and (f) SERAP. It is important to note that precipitation bias is discussed using units of millimeters per day. Therefore, the bias in millimeters per day is directly related to a bias in total precipitation. Consider the following for interpretation of the precipitation bias. If there is 1 mm/day of bias for the average precipitation for a given month and it rains 15 days on average during that month, then the bias for average total precipitation for that month is 15 mm (~0.6 inches). There are many regions of the domain where the statistically created datasets (CCR, BCSD, and SERAP, Figure 4.3d–f) tend to underestimate precipitation by between 1 and 3 mm/day. There is also a tendency for each of these datasets to overestimate precipitation in May on the Western Coast of Florida, with NARCCAP and Hostetler overestimating by the greatest amounts. The switch between tendencies to overestimate precipitation across the domain in

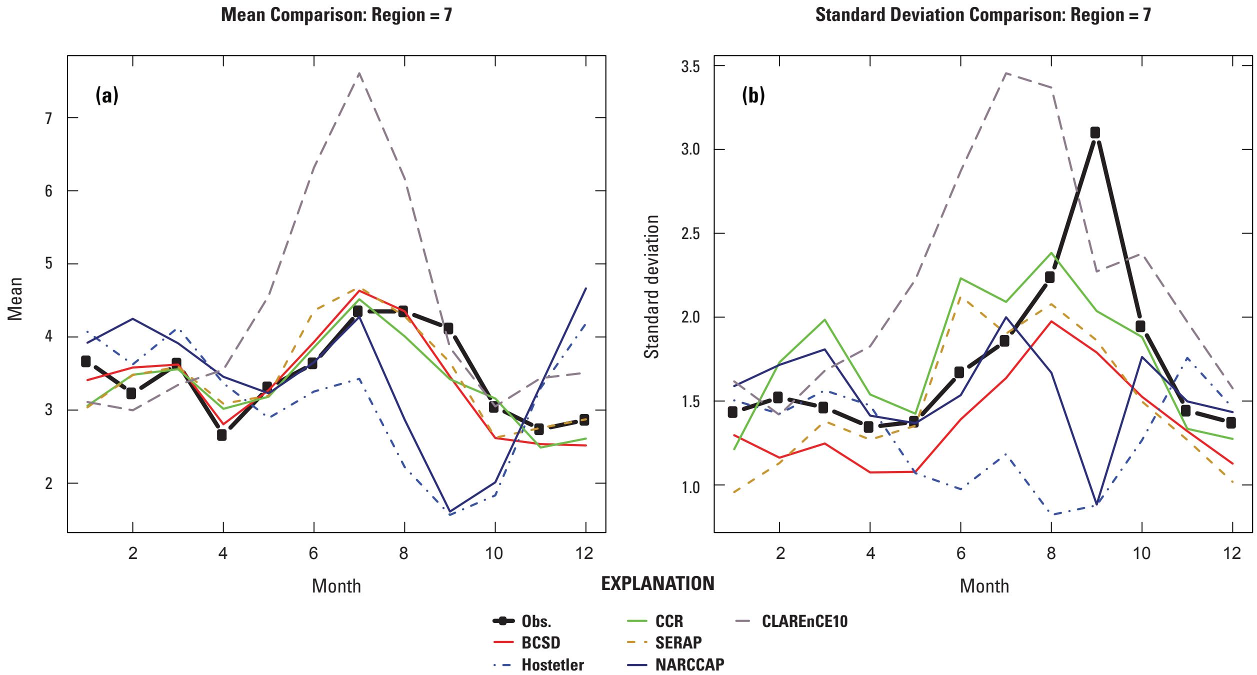


**Figure 4.6.** Annual cycle for the (a) mean and (b) standard deviation of the monthly average precipitation (mm/day) for eastern North Carolina.

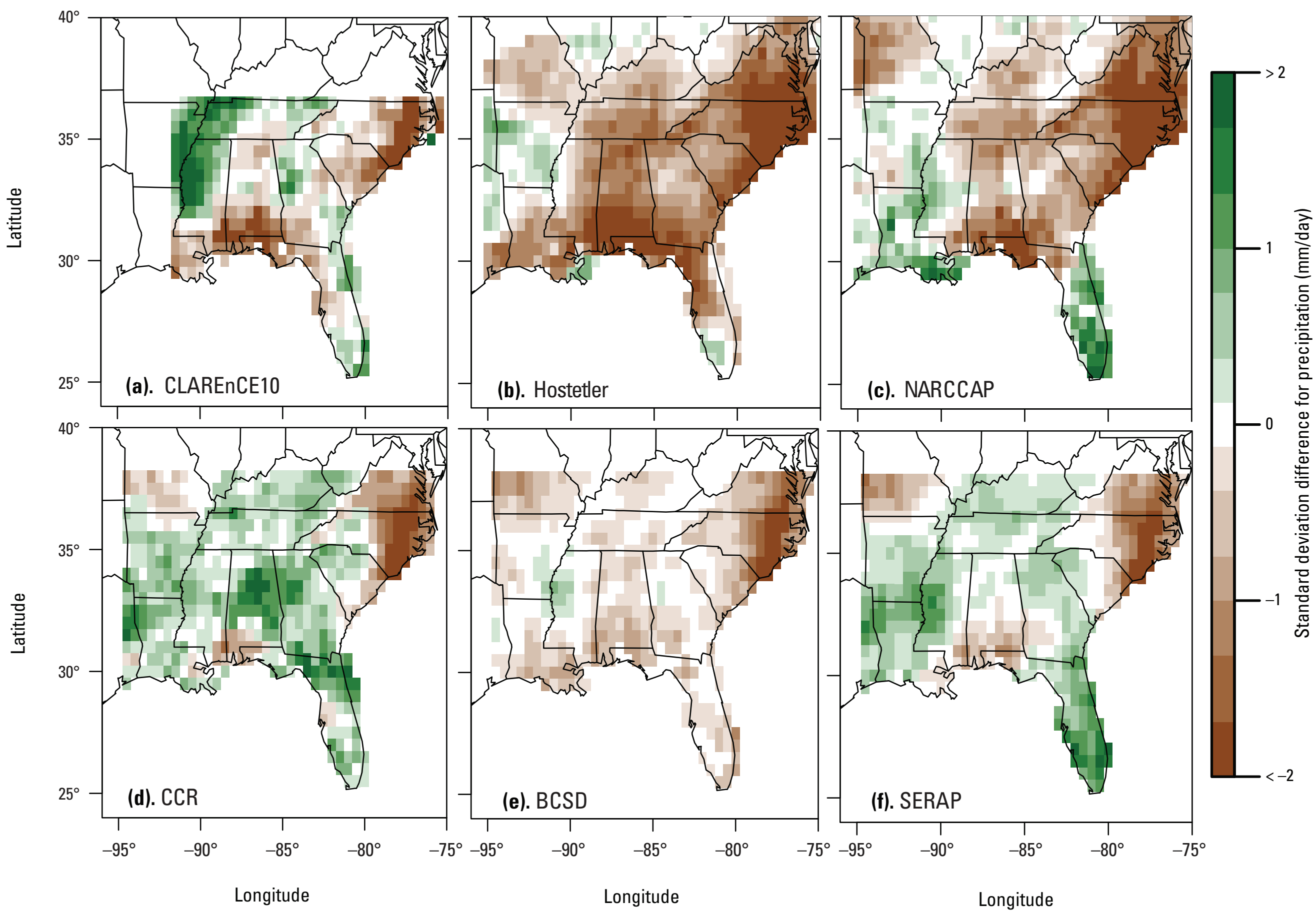


**Figure 4.7.** Standard deviation differences across the Southeast for (a) CLAREnCE10, (b) Hostetler, (c) NARCCAP, (d) CCR, (e) BCSD, and (f) SERAP for September precipitation (mm/day).

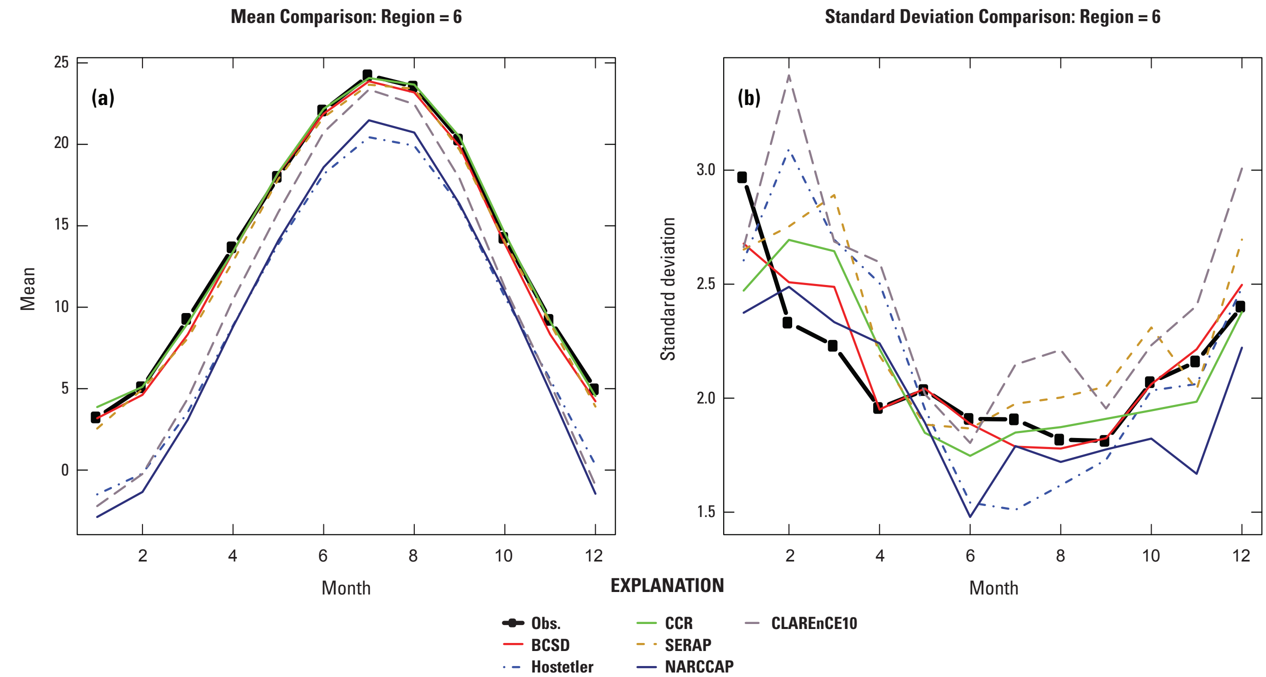


**Figure 4.8.** Annual cycles for the (a) mean and (b) standard deviation of monthly average temperature (°C) for the Southern Appalachians.

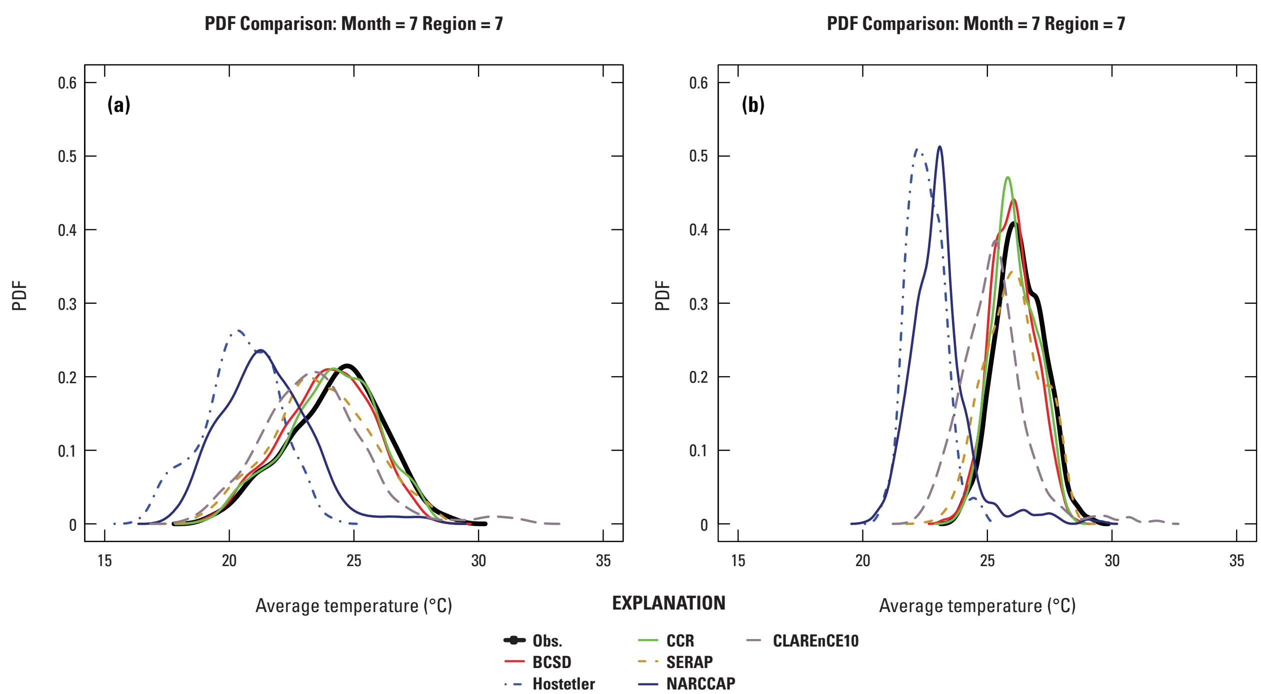


**Figure 4.9.** July probability distribution functions for temperature (°C) for (a) the Southern Appalachians and (b) Eastern North Carolina.

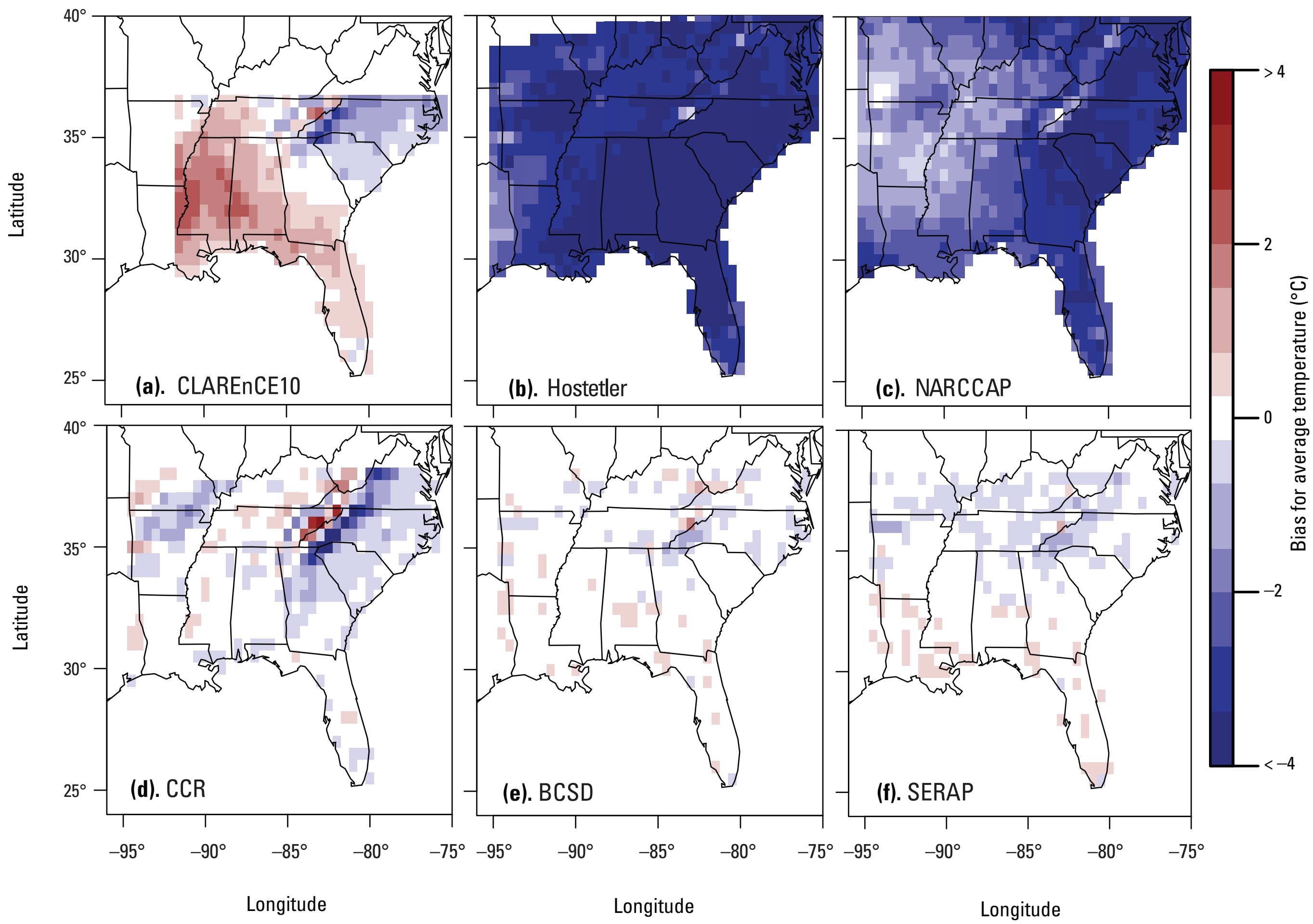


**Figure 4.10.** Bias for monthly average temperature (°C) for July for (a) CLAREnCE10, (b) Hostetler, (c) NARCCAP, (d) CCR, (e) BCSD, and (f) SERAP.

May by the dynamically created datasets to an underestimate across the domain by the statistically created datasets suggests that the bias correction inherent in most statistical downscaling techniques was possibly too rigorous in the Southeast during this time period.

A dataset should not necessarily be disqualified from use because it has bias. To show this, bias was removed from NARCCAP-downscaled data over the entire Southeast U.S. by using a simple technique. First, the difference between NARCCAP and PRISM is determined for each grid cell.. Second, the average of this difference is calculated for the Southeast U.S. This is the average bias. . Finally, the average bias is added to the difference between NARCCAP and PRISM at each grid cell to create bias corrected NARCCAP data.. This is a very simple bias-removal technique and not typically the best way of removing bias. Figure 4.4 shows the bias for monthly average temperature in September for (a) CLAREnCE10, (b) Hostetler, (c) NARCCAP, (d) CCR, (e) BCSD, and (f) SERAP. Figure 4.5 is similar to Figure 4.4 except that NARCCAP has been bias corrected with the simple technique described here. Before the bias is removed, NARCCAP shows a strong cold bias over the entire Southeast U.S. in September (Figure 4.4c). Once the bias is removed from NARCCAP-downscaled temperature, the bias for most of the Southeast U.S. is brought more in line with the temperature biases for the statistially downscaled datasets as shown in the bias for the month of September (Figure 4.5). The bias for NARCCAP in all regions for September ranges between 0–1 °C. The pattern of above and below normal temperatures seen in statistically downscaled datasets can be seen in the bias-corrected NARCCAP data.

Downscaled datasets created with dynamic downscaling are almost always provided *without* bias correction. The lack of bias correction in the raw data for dynamically created datasets leads these datasets to potentially accentuate the biases from the GCM. Depending on the GCM usedand the dynamic downscaling technique itself, the biases in the raw output of a dynamically downscaled dataset may vary from month to month and region to region in a given study domain. As such it is important to consider that raw output data taken from a dataset created with dynamic downscaling may not be bias corrected. This potential error should be considered before using a dynamically created dataset. In general, dynamically downscaled datasets should be bias corrected before they are considered for individual use so the model bias will not influence additional analyses.

Considering the information presented in Tables 4.2–4.15, it is apparent that there is a tendency for all six datasets to underestimate precipitation variability in September from South Carolina through Southeastern Virginia (specifically Regions 5, 7, and 10). In addition, there is a tendency to underestimate average precipitation in Eastern North Carolina. September is the peak of the Atlantic hurricane season, and hurricanes can contribute substantially to the annual total precipitation in the Southeast. For instance, in Eastern North Carolina, hurricanes contribute 6 to 10 percent of the annual total precipitation on average. The annual cycle for (a) monthly average precipitation and (b) the standard deviation of monthly average precipitation for Eastern North Carolina is shown in Figure 4.6. Figure 4.6a shows that the cycle for the average precipitation for each statistically downscaled dataset (CCR, BCSD, SERAP) tends to follow the observations, but the dynamically downscaled datasets have a wider spread around the observations. All these downscaled datasets tend to underestimate average precipitation in this region in September. Figure 4.6b shows that most datasets tend to capture the annual cycle for precipitation variability, but all the downscaled datasets underestimate the precipitation variability in September in this region. Figure 4.7 shows the standard deviation difference between (a) CLAREnCE10, (b) Hostetler, (c) NARCCAP, (d) CCR, (e) BCSD, and (f) SERAP and the observations for September across the study domain. Most of the downscaled datasets tend to underestimate the precipitation variability along the South Carolina coast to Southeastern Virginia and the Northern Gulf Coast, and overestimate the variability in Florida in September. Because much of Florida is a coastal region, it is subject to more thunderstorm activity associated with sea breeze in addition to hurricane precipitation. The larger errors in the standard deviation are related to the irregular extreme precipitation events associated with hurricanes. As such, the challenge associated with hurricanes for downscaling techniques is in representing the precipitation that results from hurricanes with the appropriate frequency. In literature this has proven a challenge for statistical techniques to incorporate. This is also a challenge for dynamically downscaled datasets because the lack of hurricanes in the driving GCM is translated into the dynamically downscaled output for precipitation and related variables. Therefore, although it is important to consider bias correction for dynamically downscaled datasets, it is also important in the Southeast to carefully consider how accurately any dataset reproduces the influence of hurricanes on precipitation and other related variables (winds, evapotranspiration, others).

The Southern Appalachians has the largest elevation and topographic changes of any of the regions in the Southeast U.S. As such, this region is subject to larger spatial variability in both precipitation and temperature. Given that the changes in topography and elevation in this region are not well represented in the GCMs, the input into downscaling techniques can have errors associated with topography. In the case of dynamic downscaling, the RCMs in this report have a better representation of topography than the GCMs and can correct some GCM errors in this region. In the case of statistical downscaling, some techniques will incorporate information about the topographic changes in a region, allowing these techniques to provide some correction to errors in the GCM information in this region. Regardless, the accuracy of each downscaled dataset over small areas of the mountains can vary dramatically across the Southern Appalachians, and use of these datasets in the mountains should be carefully considered in ecological modeling or conservation planning.

Topography and representations of topography by climate models and downscaling techniques are also important to consider when using a downscaled dataset. Table 4.7 provides a summary of how each dataset performs over the Southern Appalachians region. Figure 4.8 shows the annual cycle for (a) monthly average temperature and (b) standard deviation of average temperature for the Southern Appalachians for each downscaled dataset and the observations. From these two figures it seems that each dataset captures the annual cycle of average temperature and temperature variability over the entire region. For temperature variability, however, it is apparent that the downscaled datasets can have a wide spread around the observations. Figure 4.9 shows the probability distribution function (PDF) for July monthly average temperatures across the (a) Southern Appalachians and (b) Eastern North Carolina. Similarly to Figure 4.8b, the PDFs show that some downscaled datasets (NARCCAP and Hostetler in particular) have larger differences from the observations in the Southern Appalachians compared to the neighboring Eastern North Carolina region. However, it is also important to note that for both regions, the distributions can be similar to the observations or narrower. These figures and the information in the tables provide insight to how each downscaled dataset performs over the region as a whole. It is important, however, to consider that the accuracy of a dataset may be different in different areas of the Southern Appalachians because of the complex topography of the region. Figure 4.10 shows the bias for average temperature in July for (a) CLAREnCE10, (b) Hostetler, (c) NARCCAP, (d) CCR, (e) BCSD, and (f) SERAP. Although there are distinct differences among these downscaled datasets across the region, there is a consistent pattern in the Southern Appalachians. Each dataset tends to underestimate the average temperature on the east side of the mountains, and overestimate (or have less of an underestimation) on the west side of the mountains. This pattern is not shown by Figures 4.8 and 4.9 or the earlier tables, but is important to consider for using these downscaled datasets in this region.

No single downscaled dataset best represents all the aspects of temperature and precipitation across the entire report domain. As shown in Tables 4.2–4.15, in most cases no one downscaled dataset is consistently most accurate for all the metrics and variables over the entire Southeastern region. Some downscaled datasets better represent one or both variables studied in individual regions. Accordingly, it is important that the choice to use a particular downscaled dataset is made within the context of the natural resource decision or impact assessment. That is, *what climate and climate change attributes are most (or are thought to be most) relevant to the decision or impact assessment made?* Datasets differ with respect to the variables available and in the fidelity of those variables to observations.

Our results and experience from working with and analyzing these data lead to three clear primary recommendations for managers, ecologists, and others with a need to select and use downscaled datasets for ecological modeling, assessments, and related decision support.

- **Consult a climatologist familiar with climate models and downscaling**—Climatologists familiar with climate models and downscaling possess a knowledge base that can be useful to an ecologist when selecting appropriate datasets. These climatologists will be aware of the differences described in this report and can assist ecologists when selecting one or more downscaled datasets for use in studies of ecological or conservation impacts. Recommendations of appropriate climatologists to work with can be provided by the authors or the Department of the Interior Southeast Climate Science Center.

- **Use more than one downscaled dataset—**Each downscaled dataset has its own strengths and weaknesses. Using multiple datasets (also known as an ensemble) allows the weaknesses in each model to be addressed by incorporating a range of possible scenarios. Using an ensemble mean also allows the best and worst case possibilities to be considered. Ideally, all available datasets should be used in order to fully characterize the internal and structural uncertainties of the downscaled projection for each scenario (Mote and others, 2011), including multiple emissions scenarios to fully characterize the uncertainty associated with human actions.

- **If it is only feasible to use one downscaled dataset, consider the best possible one for all sensitivities**—As mentioned previously, no one downscaled dataset will provide the highest accuracy for every metric for every variable. Therefore, it is important to consider what aspect of climate has the largest influence on the species and (or) ecosystem of interest and which downscaled datasets best represent these sensitivities.

These recommendations should be considered when deciding which downscaled datasets to use. Given the complexities of different downscaling techniques and the resulting differences in accuracy among downscaled datasets, we recommend engaging a climatologist during the process of modeling. Discussions with a climatologist about critical sensitivities in the ecosystem of interest can assist with the selection of the best data to use and help ensure that the climate model deficiencies and uncertainties are more fully understood.

# 5 Conclusions and Recommendations

The previous sections discussed the results of the initial evaluation of each of the six datasets and a comparison of the available information and literature regarding these datasets. This analysis details results for the annual cycle and probability distribution functions (PDFs) for each region and spatial analysis of the bias and standard deviation difference for the Southeast for each month. The main narrative of this analysis, however, focuses on highlighting important differences with regard to the impacts to ecology and conservation decisionmaking in the Southeast U.S. Appendixes 2, 3, and 4 include all other figures and tables related to the evaluation of these datasets. Appendix 2 contains the 50 and 15 km resolution maps of bias and standard deviation difference. Appendix 3 contains plots of the annual cycles, including the root mean square error and correlation for each dataset and for each region, and Appendix 4contains the PDFs for each region. Given that this report was separated into two sections, downscaled dataset summary and downscaled dataset evaluation, this section will summarize the conclusions from each section separately. The recommendations of the report will be discussed at the end of this section.

## 5.1 Downscaled Dataset Summary

Section 2 summarized the differences among six available datasets and provided context regarding the needs for ecological modeling in the Southeast. From this synthesis several conclusions can be drawn regarding the ability of downscaling techniques as shown in literature.

- **Downscaled datasets have different temporal and spatial resolutions:** Although the desired temporal scales of these datasets are not shown in ecological literature, all of these datasets have coarser spatial resolution than recommended by ecological literature, particularly for mountainous terrain. It is important to note, however, that the most useful spatial resolution for a downscaled dataset will vary depending upon the application. For instance, resolutions finer than 10 km are needed in some, but not necessarily all, instances to provide robust results in ecological modeling. In cases where a downscaled dataset with a resolution finer than 10 km is required, some method of resampling may also be used rather than considering a downscaled dataset finer than 10 km. Resampling refers to a variety of methods for estimating the precision of various sample statistics. For instance, resampling includes bootstrap techniques, which takes samples with replacement from the original data to provide an estimate of the distribution of a variable where there is a lack of information.

- **Extremes and Statistical Downscaling Techniques:** Transfer functions such as those used to create the

SERAP and BCSD datasets are shown in literature to provide a good estimate of changes in average conditions, but tend to lack representation of the observed climate variability and extremes. The technique in SERAP produces a better representation of extremes in the output than the BCSD approach as shown in literature.

- **Computational Expense of Dynamic Downscaling:** Datasets created with dynamic downscaling techniques (CLAREnCE10, Hostetler, NARCCAP) capture more of the physics of the atmosphere; however, the expense of computation reduces the number of emissions scenarios, GCMs, and model years.

- **Statistical Downscaling and Number of Variables:** Given that statistical downscaling techniques depend on an observed record of the variable of interest, most downscaled datasets created with statistical techniques focus on temperature and precipitation because they have long records (> 20 years) in station and gridded observation datasets.

## 5.2 Downscaled Dataset Evaluation

Section 3 focused on the results of an initial evaluation of six downscaled datasets over the Southeast U.S. Given the evaluation of these six datasets, several conclusions can be drawn from the previous results and discussion.

- **Bias Correction:** Each of the downscaled datasets created with dynamic downscaling (CLAREnCE10, Hostetler, NARCCAP) inherit the errors of the driving GCM and will show significant biases in the raw data. These results indicate a need for bias correction of these datasets prior to use in ecological modeling. However it is important to note that downscaled datasets created with statistical downscaling (CCR, BCSD, SERAP) also inherit the errors of the GCM, and some of the GCM errors will be reflected in these datasets also.

- **Hurricanes:** Given the resolution of most GCMs (> 100 kilometers ), the precipitation associated with hurricanes is approximated, or parameterized, and not explicitly represented in the GCM. Because every downscaling technique begins with information from the GCM, this leads to errors with regard to the variability of precipitation during the peak of the Atlantic hurricane season. In some places the variability is overestimated (Florida), while the variability is strongly underestimated in other places (North Carolina, Northern Gulf Coast).

- **Complex Topography:** Changes in topography and elevation in the Southern Appalachians are not well represented by GFDL, and this is also true of the downscaled datasets. There are challenges representing temperature and precipitation in this region.

- **There is no "best" downscaled dataset:** There is no single downscaled dataset that best represents all the aspects of temperature and precipitation across the entire report domain. However, there are some downscaled datasets that better represent one or both variables studied in individual regions.

## 5.3 Recommendations

The summaries, results, and discussion presented in this report have led to several conclusions,which in turn has lead to several recommendations for the use of downscaled datasets in ecological modeling and decisionmaking.

**(1) Consolidate what is known regarding the critical sensitivities of Southeast species.** There are only a few studies in the Southeast that assess the impact of climate change to individual species and provide information regarding the sensitivities of an individual species to current climate variability. This lack of information has been acknowledged in the Southeast Technical Report for the National Climate Assessment, but is also acknowledged by the Science and Technical Advisory Committee of the North Carolina Department of Environment and Natural Resources (2008). Therefore, it is recommended that the information from studies regarding the climate sensitivities of individual species be consolidated and made available to ecological and climate modelers as well as conservation planners.

**(2) Evaluation of downscaled datasets should be considered broadly.** Evaluation of these datasets should consider averages of at least temperature, precipitation, and winds, but should also include averages of evapotranspiration and (or) humidity where possible. Because there are different thresholds for different individual species, the evaluation of extremes should examine the accuracy of the entire distribution of values, rather than individual thresholds.

**(3) Additional evaluation is needed.** This initial evaluation focused on temperature and precipitation, but ecologists in the Southeast have indicated a need for information about the accuracy of winds, evapotranspiration, and drought conditions in these datasets as well as a finer temporal resolution. Therefore, it is recommended that this evaluation be repeated for data at a daily timescale for multiple variables and thresholds of variables (i.e., number of days with temperature greater than 32 ºC), but also with multiple GCMs included where possible.

**(4) Further engagement among the climatology community, ecologists, and conservation managers should be encouraged.** It is important to consider that the results of the evaluation in this report provide a basic guide to the accuracy of each of these datasets. Therefore, the engagement between these groups can allow the needs of ecologists and conservation managers to be effectively addressed by climatologists. In addition, the engagement process can also allow the needs of climatologists to be addressed by ecologists and conservation managers in the Southeast. At local levels, this engagement can be promoted by the Landscape Conservation Cooperatives (LCCs) by highlighting relevant studies that are collaborative in nature between climatologists and ecologists/natural resource managers. In addition, both the LCCs and SECSC can actively work to connect ecologists interested in using downscaled datasets to climatologists familiar with these datasets. This could be done by promoting an online directory of such climatologists or by facilitating collaborative efforts between the scientific communities that also engage and work with natural resource managers.

## 5.4 Acknowledgments

The authors thank the Department of Interior Southeast Climate Science Center (Grant number G12A20515) for funding this report. The authors also thank the members of their Client Advisory Team for providing guidance in the creation of this report. The team members include

- Rua Mordecai, South Atlantic Landscape Conservation Cooperative
- Jayantha Obeysekera, South Florida Water Management Division
- Laurie Rounds, NOAA Office of Ocean and Coastal Resource Management – Coastal Programs Division
- Laura Thompson, National Climate Change and Wildlife Science Center
- John Tirpak, Gulf Coastal Plains Ozarks Landscape Conservation Cooperative
- Steve Traxler, Peninsular Florida Landscape Conservation Cooperative

We also thank the participants of the Regional Climate Variation and Change for Terrestrial Ecosystems Workshop for providing insights and knowledge regarding appropriate variables and metrics to evaluate for ecologists, as well as their thoughts on further engagement between the climate science and ecology communities in the Southeast U.S.

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# Appendix 1. Workshop Summary

## Regional Climate Variations and Change for Terrestrial Ecosystems Workshop: Summary

North Carolina State University, the University of North Carolina at Chapel Hill, and the U.S. Environmental Protection Agency in partnership with the U.S. Department of the Interior Southeast Climate Science Center hosted the Regional Climate Variations and Change for Terrestrial Ecosystem Workshop. The workshop was held at N.C. State University in Raleigh on May 16–17, 2013. The workshop brought together approximately 40 scientists, mostly from the Raleigh–Durham–Chapel Hill area, to discuss challenges and uncertainties of understanding the interactions of climate and ecosystems across the Carolinas. This multidisciplinary effort sought to bridge the knowledge gap between climate scientists and ecosystem scientists. To create a foundation, high-level scientific presentations were given from both disciplines.

The first day of the workshop included an open discussion between participants and speakers on climate data and uncertainties. Climate presentations focused on data needs for ecosystem scientists and included talks on global climate modeling, dynamic and statistical downscaling, and synthesizing currently available climate change projections. The open discussion on climate model projections and datasets provided expert guidance on using climate change projections for ecosystems applications. Ecosystem scientists are seeking climate scientists who can provide expert guidance on how to properly use global climate models (GCMs) and downscaled climate change projection data. Currently, there is some disconnect between the disciplines and the potential misuse of climate change projection information. Ecologists stress other anticipated changes in the future, such as urbanization, are likely more important than climate change for the Carolinas. Ecologists suggested that future decisions about climate change should also consider the influence of the human component changes on the local climate.

The first half of the second day included presentations on terrestrial ecosystem modeling and a panel discussion about integrating climate and ecosystems. Similar to the first day, ecologists provided presentations to help climate scientists understand ecosystem needs and challenges. The presentations focused on different ecosystem modeling techniques, uncertainties associated with ecosystem modeling, and a few examples of climate adaptation practices for ecosystem decisions with respect to climate change. The first discussion sessions provided a sense of the needs for ecosystem scientists. In general, considering the impact of a changing climate on ecosystems is considered a “wicked” problem because there is an urgent need to make decisions that are informed by model frameworks that have large uncertainties. In particular, it has been identified that model errors propagate and grow as the model framework becomes more complex. Ecologists acknowledge that expert assessments are used to make informed decisions relating to climate change; however, there is a need for more quantitative assessment of climate change for ecosystems. The quantitative assessment is hindered by the lack of ecological data and basic biological research relating climate sensitivities to species and ecosystems.

During lunch on the second day, a demonstration of the USGS Geo Data Portal (*http://cida.usgs.gov/gdp/*) was provided by David Blodgett (IT Specialist and Project Manager, USGS Center for Integrated Data Analytics). The demonstration focused on illustrating the availability and capability to access different datasets through the Geo Data Portal. The datasets available include downscaled climate change datasets, topographic information, and projections of sea level rise. The Geo Data Portal, however, does not indicate the accuracy of the downscaled climate change datasets. This underscored the need for more guidance and interaction between climate scientists and ecologists.

The final discussion on the second day focused on two aspects of the needs of ecologists with regard to climate change information and research priorities. The general needs of ecologists with regard to climate information were first discussed followed by determining the climate sensitivities that are most important to ecological applications in the Southeast. During the discussion, ecologists identified that extreme weather events and potential changes to the spatial and temporal distribution of those events are important for ecosystems. The extremes mentioned most often by the group included temperature extremes, rainfall extremes, and storm frequency. Ecologists also identified that the downscaling does not provide the resolution needed for many applications, and interpolation typically is used to supplement downscaled data. For instance, topoclimatic models are applied to increase the resolution of downscaled climate change datasets. However, climate scientists stress that these techniques are not appropriate for extremes or spatially discontinuous variables such as precipitation.

As part of the discussion, climate scientists attempted to compile a list of model metrics that can be used to evaluate currently available downscaled climate change datasets over recent history. Defining a comprehensive list is difficult, because model metrics can be species/application specific and the relation between species and climate variability often is uncertain. In addition to the frequency of extreme events, there is interest in more specialized output, including evapotranspiration and vapor pressure deficit. The specificity with regard to the climate sensitivity of an ecosystem or species, however, was not identified. This mirrors current ecological literature regarding the climate sensitivities of given species and ecosystems. From these discussions several recommendations were produced by the workshop participants.

- More solicitations on collaborative research between ecosystems scientists and climate modelers on discrete decision-based projects are encouraged.
- There is a need for more documentation and guidance from the climate science community regarding:
    - Appropriate use of downscaled climate change datasets
    - Error/uncertainty propagation in climate modeling
    - Basic metadata differences (spatial domain, spatial resolution, temporal resolution, time periods, etc.) between downscaled datasets
- There is a need for more basic ecology/biology research regarding the climate sensitivities of different species and ecosystems.
- Integrating climate data with land-use/cover change information.
- Further engagement is encouraged among the ecologists, hydrologists, biologists, managers, and climate scientists through similar workshops held at least annually.

It was recognized by the group that some decisions cannot use a small project decision-based approach and require urgent and immediate action for resilient decisions integrating climate change information. In those instances, scientists must rely on the best available data for decisions. Therefore, documenting the strengths and weaknesses of available climate data and providing accessibility to experts on these data for guidance was a key recommendation of this workshop. The workshop participants recommended further engagement through annual or biannual workshops with the larger community of ecologists and climate scientists. Specifically, the participants requested that future workshops provide updates on the state of the respective scientific fields to include discussions of priority needs.

# Appendix 2. Bias and Standard Deviation Difference Maps 50 and 15 km Resolutions

[Appendix 2 available for download at *http://pubs.usgs.gov/of/2014/1190/*]

In Chapters 3 and 4, the bias and standard deviation difference were used with 50 km resolution maps as part of the discussion of downscaled datasets across the Southeast U.S. In this appendix, both 50 km and 15 km resolution maps are shown for the bias and standard deviation difference from monthly temperature and precipitation for each month across the domain.

# Appendix 3. Annual Cycles for All Subregions

[Appendix 3 available for download at *http://pubs.usgs.gov/of/2014/1190/*]

In previous chapters of this report, the annual cycles were discussed for the mean and standard deviation of monthly temperature and precipitation for several subregions in the Southeast U.S. In this appendix, all the annual cycles for monthly temperature and precipitation are included for each subregion. In addition, the root mean square error and correlation for each variable are also included in tables following each group of figures.

# Appendix 4. Probability Distribution Functions (PDFs) for All Subregions

[Appendix 4 available for download at *http://pubs.usgs.gov/of/2014/1190/*]

In Chapters 3 and 4, the distribution of temperature and precipitation was discussed through the use of probability distribution functions (PDFs). While some examples were provided in Chapters 3 and 4, this appendix provides all the January and July PDFs for temperature and precipitation in each of the 14 subregions discussed in the earlier chapters. Recall that PDFs are unitless value but represents the frequency with which a value of temperature or precipitation occurs.

For additional information regarding this publication, contact:

Director,
DOI Southeast Climate Science Center
Department of Applied Ecology
127 David Clark Labs
North Carolina State University
Raleigh, NC 27695-7617

Or visit the Southeast Climate Science Center
Web site at:
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Prepared by:
USGS Science Publishing Network
Raleigh Publishing Service Center
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Raleigh, NC 27607

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Wootten and others—**Downscaled Climate Projections for the Southeast United States**—Open-File Report 2014–1190