CHAPTER 17

Florida Climate Variability and Prediction

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This chapter describes the sources and mechanisms for climate variability in Florida across timescales (i.e., seasonal-to-decadal) and how they are used to make predictions. Current capabilities in terms of prediction quality, with an emphasis on precipitation and land surface temperature on seasonal timescales, are introduced as well as challenges and opportunities for the future. The longer decadal time scales are discussed in the next chapter in conjunction with climate change associated with anthropogenic forcing.

Key Messages

- There is known large-scale climate variability (e.g., El Niño) that affect Florida's local climate.
- While this large-scale climate variability can be predicted several months in advance, correctly capturing the regional impacts remains challenging.

Keywords

Multi-model ensembles; Regional climate prediction; Dynamical downscaling; Statistical downscaling

A Scientific Basis for Regional Climate Prediction – Global Drivers of Regional Florida Climate Variability

Florida's climate, including rainfall and temperature, is influenced by many modes of natural variability. Some of these modes are more significant than others; for example, the El Niño Southern Oscillation (ENSO), the Atlantic Multi-decadal Oscillation (AMO), and the Pacific Decadal Oscillation (PDO) have the strongest influence on Florida's climate variability. Other modes do influence Florida's climate, such as the North Atlantic Oscillation (NAO)/Arctic Oscillation (AO) and the solar cycles, but their impact is not as well known. These naturally occurring modes of variability impact Florida by their modification of global circulation anomalies, in particular, the subtropical and polar jet streams. In this section, we describe these modes of climate variability and their imprints on Florida's climate. The subsequent sections will show how these modes of variability can be used to provide the scientific basis for short-term climate prediction on regional scales. Additional information on Florida's climate and its drivers can be found in Misra et al. (2011), Obeysekera et al. (2011a), and Obeysekera et al. (2011b).

El Niño Southern Oscillation (ENSO)

The El Niño Southern Oscillation (ENSO) is characterized by large-scale atmosphere–ocean interaction in the Tropical Pacific, in which a 2- to 10-year oscillation of warm, neutral, and cool sea surface temperature anomalies (SSTAs) exists (Rasmusson and Carpenter 1982; Philander 1983; Rasmusson and Wallace 1983; Trenberth 1997; Cobb et al. 2003; among many others). These oscillatory swings in SSTAs are referred to as El Niño (warm phase), La Niña (cold phase), and neutral. El Niño and La Niña phases typically persist for 6 to 18 months. Though the center of SSTA activity for an El Niño or La Niña event is in the Tropical Pacific, the imprints of these events can be seen globally. As the tropical sea surface temperatures (SSTs) change, the location of tropical convection shifts, which in turn leads to large-scale, global changes in the atmospheric circulation that can alter temperatures, humidity, winds, clouds, and more (Alexander et al. 2002). For example, during an El Niño event (warm Tropical Pacific), warm SSTAs force evaporative anomalies leading to anomalous rainfall. These rainfall anomalies can be thought of as an atypical tropical heat source (or anomalous tropical forcing) in the middle of the atmosphere, which produces a Rossby wave response that reaches into the extra tropics (Sardeshmukh and Hoskins 1988; Trenberth 1997; Barsugli and Sardeshmukh 2002; Straus and Shukla 2002; among many others). This "teleconnection" of the Tropical Pacific to the North Pacific is sometimes referred to as "The Atmospheric Bridge" (Alexander et al. 2002). In turn, anomalous tropical heating (or forcing) leads to impacts in atmospheric circulation fields across the globe, but particularly influences climate over North America. Anomalous tropical forcing is strongest in winter, as this coincides with the mature stage of events, and teleconnections are often strongest in winter (January-March, or JFM), as well (Trenberth et al. 1998). Though ENSO has a periodicity of 2-10 years, the impacts can be seen on timescales ranging from sub-seasonal (on the order of 10 days; e.g. Hudson et al. 2011; Rasmussen et al. 2015, though these results are not specific to North America) to seasonal (on the order of three months) and longer (Trenberth et al. 1998). ENSO teleconnections are far-reaching; however, the southern US, including Florida, is a key zone of strong association with ENSO forcing (Ropelewski and Halpert 1986).

Numerous references discuss the influence of ENSO on Florida's climate. The influence of El Niño (La Niña) on precipitation manifests as an increase (decrease) in wintertime precipitation (Gershunov and Barnett 1998a; Gershunov 1998; Goly and Teegavarapu 2014; Nag et al. 2014), and the influence of El Niño (La Niña) on wintertime temperature is cooling (warming). However, these impacts vary seasonally and spatially (see Table 17.1 adapted from the Florida

Climate Center and Fig. 17.1). Fig. 17.1 depicts the observed composite precipitation[1] anomaly over the southeastern US during JFM and July-August-September (JAS) El Niño events and La Niña events for the period 1982–2009. The strongest anomalies are seen during winter season El Niño and La Niña events, while the summer season shows a mixed, weak response; hence, we separately consider JFM and JAS. A similar assessment for 2 m temperatures[2] is illustrated in Fig. 17.2 where we see the strongest response is for JFM El Niño events, while the remaining composites show only a weak response to El Niño and La Niña events. Because of the strong teleconnection in the winter season, an El Niño or La Niña event leads to predictability of temperature and precipitation over the southeast US and Florida, although there is less predictability in summer months due to the weak response in the region. This notion is discussed later in this chapter.

The mechanism for the southeastern US response to warm tropical forcing is that changes in Tropical Pacific convection lead to a shift in the subtropical jet stream causing moisture to be advected across the region, and a trough in the midlatitude jet stream across the southeast allows precipitation in the region (Ropelewski and Halpert 1986; Leathers et al. 1991; Zorn and Waylen 1997). In contrast, during a La Niña event, there is poleward displacement of the midlatitude jet leading to zonal airflow and drying over the region (Ropelewski and Halpert 1986). The relevant 500 mb circulation anomalies are depicted in Fig. 17.3 for winter and summer El Niño and La Niña[3]. The strongest circulation response is seen in wintertime El Niño and La Niña, consistent with the strong response in temperature and rainfall patterns depicted in Figs. 17.1 and 17.2. In contrast, circulation anomalies are very weak in the summer season and during neutral years (neutral years not shown). While this pattern may be similar to the Pacific North American (PNA) teleconnection pattern, there is an important distinction. The positive (negative) PNA pattern tends to be associated with El Niño (La Niña) events, however the ENSO-forced and PNA teleconnection may be distinct (for further information, see Straus and Shukla 2002).

Table 17.1. El Niño, La Niña impacts for the four seasons (OND, JFM, AMJ and JAS) in Florida. Adapted from the Florida Climate Center Office of the State Climatologist (https://climatecenter.fsu.edu/topics/climate-variability).

<table>
<tr><th>Phase</th><th>Region</th><th>OND</th><th>JFM</th><th>AMJ</th><th>JAS</th></tr>
<tr><td rowspan="2">El Niño</td><td>Peninsular Florida</td><td>Wet
Cool</td><td>Very Wet
Cool</td><td>Slightly Dry</td><td>Slightly Dry or No Impact</td></tr>
<tr><td>Western Panhandle</td><td>No Impact</td><td>Wet</td><td>Slightly Dry</td><td>No Impact</td></tr>
<tr><td rowspan="2">La Niña</td><td>Peninsular Florida</td><td>Dry
Slightly Warm</td><td>Very Dry
Warm</td><td>Slightly Wet</td><td>No Impact</td></tr>
<tr><td>Western Pan-handle</td><td>Slightly Dry</td><td>Dry</td><td>Dry</td><td>No Impact</td></tr>
<tr><td>Neutral</td><td>All Regions</td><td>No Impact</td><td>No Impact</td><td>No Impact</td><td>No Impact</td></tr>
</table>

[1] C CPC Unified Gauge-Based Analysis of Daily Precipitation over CONUS (Xie et al. 2010)

[2] GHCN-CAMS Gridded 2 m temperature over land (Fan and van den Dool 2008)

[3] NCEP-DOE Reanalysis 2 (Kanamitsu et al. 2002)

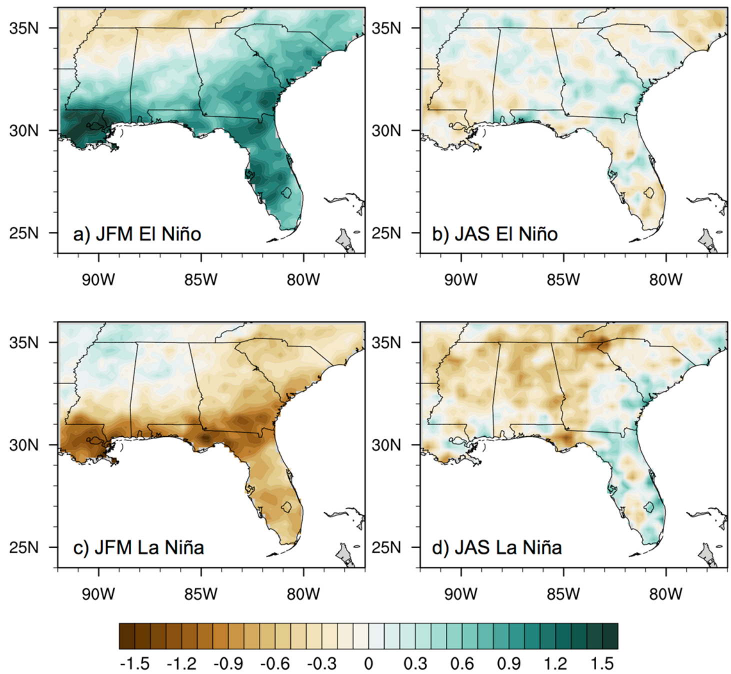

Figure 17.1. 1982–2009 precipitation anomalies (mm/day) during (a) JFM El Niño events, (b) JAS El Niño events, (c) JFM La Niña events, and (d) JAS La Niña events.

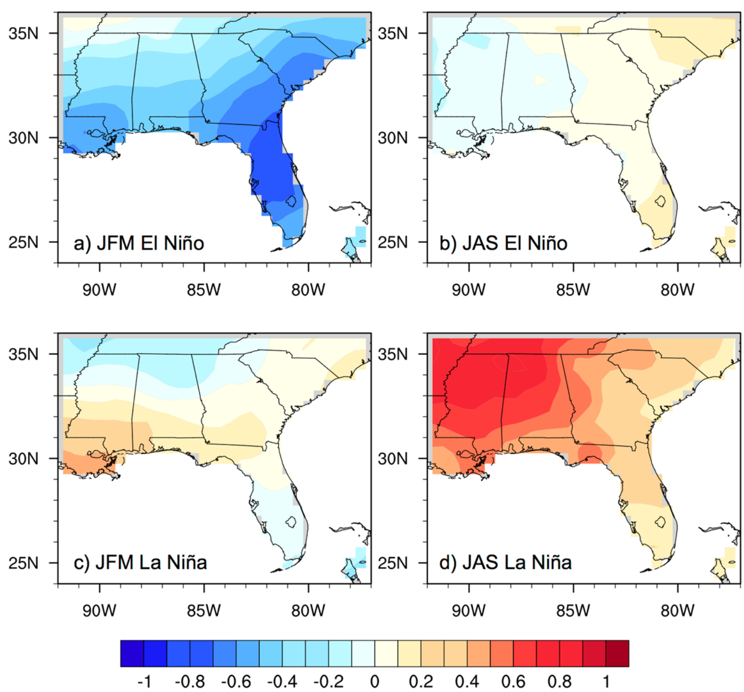

Figure 17.2. As in Fig. 17.1, but for 2 m temperatures.

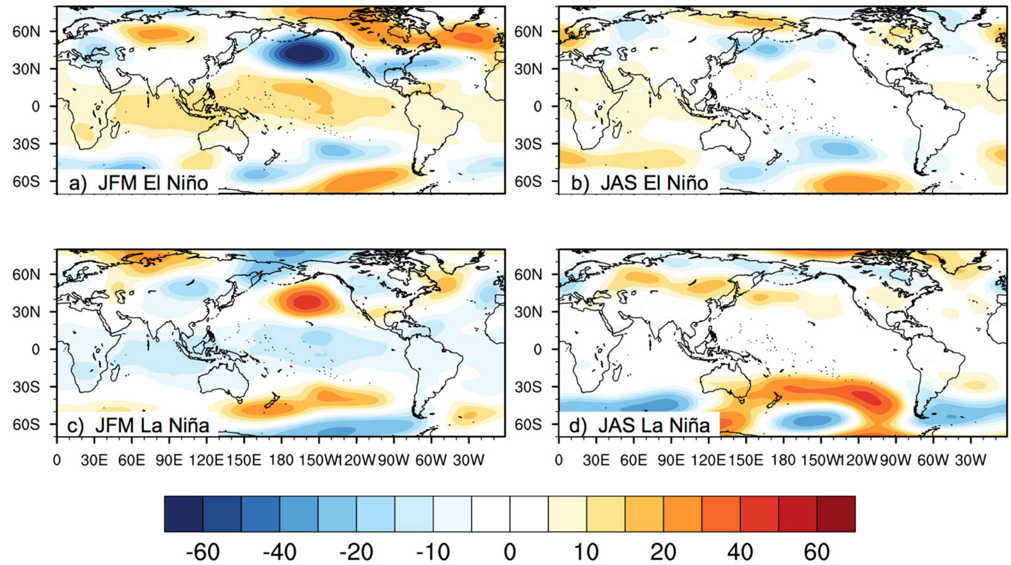

Figure 17.3. As in Fig. 17.1, but for 500 mb heights in meters.

The Pacific Decadal Oscillation

The Pacific Decadal Oscillation (PDO) is sometimes described as a long-lived, "El Niño-like" pattern of Pacific climate variability, and it is a natural mode of variability active on decadal timescales (e.g. Mantua and Hare 2002). Though ENSO and the PDO have similar spatial characteristics, they are very different in their time characteristics; where ENSO events persist for six to 18 months, PDO events persist for 20 to 30 years (but they can be sometimes as short as five years). While the SST signatures for the PDO and ENSO are very similar, the PDO shows strong SSTAs in the North Pacific and a weaker tropical signature, opposite to ENSO. The PDO index can be seen in Fig. 17.4[4]. As the PDO SST signature is very similar to ENSO, the imprints on Florida's climate are also very similar, but they occur across a longer timescale (Misra et al. 2011). Again, this relationship is primarily seen in the winter season, namely November through April (NDJFMA). The correlation of NDJFMA precipitation and temperature over Florida with the PDO index is illustrated in Fig. 17.5., which shows similarities in precipitation and temperature during ENSO events. We also see a strong positive correlation between PDO and precipitation and a weaker negative correlation between PDO and 2 m temperatures.

While the PDO and ENSO are distinct phenomena acting on different timescales, there is evidence of interaction between active PDO and ENSO phases. For example, when the PDO and ENSO are in phase (i.e. both are warm or cold), they constructively interfere, and when they are out of phase (i.e. one is cold and the other is warm, or vice versa), they destructively interfere (Gershunov and Barnett 1998b; Fuentes-Franco et al. 2016). During the destructive phase, ENSO

[4] http://ds.data.jma.go.jp/tcc/tcc/products/elnino/decadal/pdo.html

signal over the US is distorted, and it is strengthened during the constructive phase (Gershunov and Barnett 1998b). Overall, while the relationship between Florida precipitation or temperature and the PDO may be weaker than that between Florida precipitation or temperature and ENSO, it still explains about 25% of interannual dry season rainfall variability, making it a key player in Florida's climate variability.

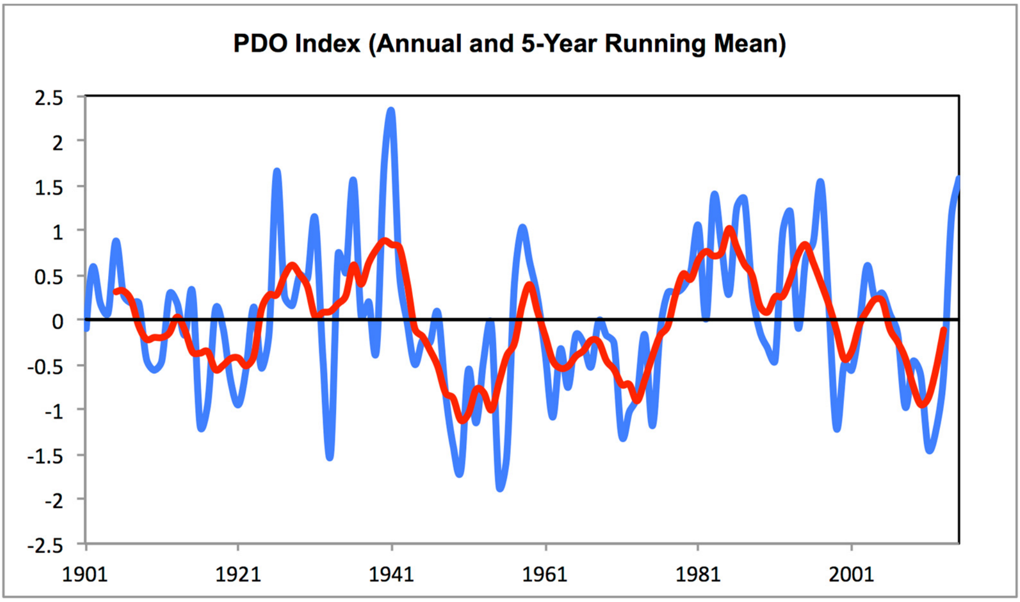

Figure 17.4. The PDO index. Annual means are depicted in blue, and 5-year running mean in red. Averages are defined at the center of each five-year period. This time series uses data from http://ds.data.jma.go.jp/tcc/tcc/products/elnino/decadal/pdo.html

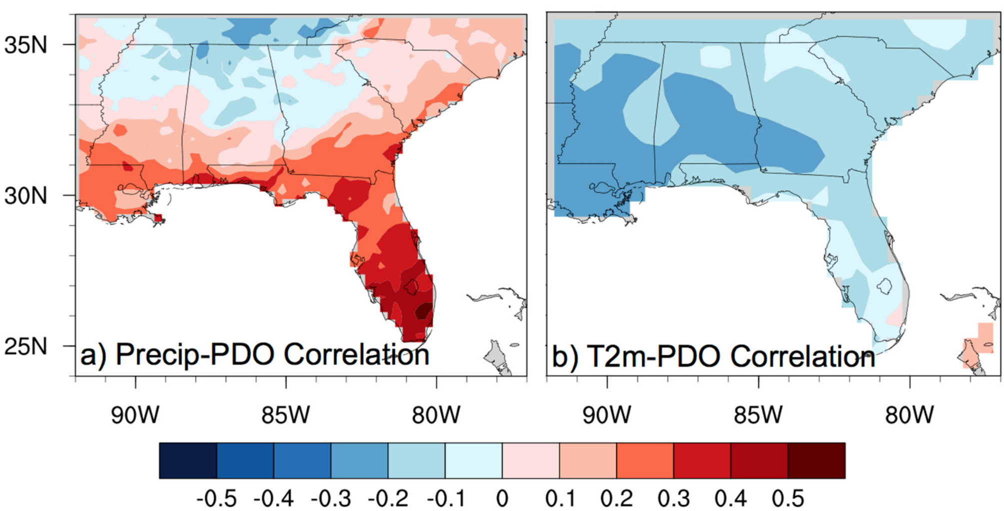

Figure 17.5. Correlation of the PDO index (see Fig. 17.6) with precipitation and temperature over Florida. The time period considered is NDJFMA from 1951 to 2010.

The Atlantic Multi-Decadal Oscillation

The Atlantic Multi-Decadal Oscillation (AMO) is a naturally occurring fluctuation in North Atlantic SSTs, characterized by a 65- to 70-year oscillation (Schlesinger and Ramankutty 1994). Traditionally, the AMO index is based on 10-year average SST anomalies in the North Atlantic, with the northern boundary at 60N (Enfield et al. 2001). The cool and warm phases of the AMO have a difference of about 1 °C. Shifts in the AMO cycle have been occurring for at least the last 1,000 years. While the AMO is an important feature in the long-term climate cycle, predicting it is difficult, as most climate models cannot skillfully predict when the AMO will change and they have difficulties simulating the AMO structure (Ruiz-Barradas et al. 2013). However, the AMO is one of the major contributors to multi-decadal variability over Florida.

While the AMO is a very long-term SST pattern that may not lead to year-to-year shifts in rainfall or temperature over Florida, the influence of this mode of climate variability can be seen across the globe (Knight et al. 2006). AMO SST anomalies most significantly influence summer precipitation over North America (i.e. June through August, or JJA) (Sutton and Hodson 2005), and the influence can be seen on Florida precipitation and temperature (Morss et al. 2005). Although the AMO is difficult to predict, its impacts on decadal-scale variations in summertime North American precipitation are consistent in observations and climate models when climate models represent the AMO (e.g. Schubert et al. 2009). Florida is no exception, and the influence can mainly be seen on summertime precipitation (Enfield et al. 2001) and Atlantic hurricanes (Trenberth and Shea 2006). Studies have shown that wintertime Florida precipitation shows no significant correlation with the AMO (Moses et al. 2013). At least twice as many tropical storms mature into hurricanes during AMO warm phases compared to AMO cold phases (Misra et al. 2011).

Analysis of precipitation extremes has shown that rainfall in South and Central Florida is more plentiful (less plentiful) during warm (cold) AMO phases (Enfield et al. 2001; Curtis 2008; Teegavarapu 2012). Florida precipitation, particularly in Central Florida, is in phase with the AMO. Fig. 17.6 shows the 10-year running mean Central Florida precipitation anomalies from 1905 to 2010[5] (top) and the 10-year running mean AMO index[6] (bottom) (Figure adapted from Enfield et al. 2001). The main signatures for the AMO can be seen for summertime precipitation over Florida; however, Moses et al. (2013) noted that the AMO can also account for some temperature variability in summertime (daytime high temperatures) in Miami, Fort Lauderdale, and Belle Glade (about 15 to 20%).

Hu et al. (2011) discussed the influence of the AMO on large-scale circulation fields, focusing on the summer season impacts on North American Precipitation. During the warm phase, there

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[5] NOAA National Centers for Environmental information, Climate at a Glance: U.S. Time Series, Precipitation, published October 2016, retrieved on October 13, 2016 from http://www.ncdc.noaa.gov/cag/

[6] AMO smoothed long time series accessed from http://www.esrl.noaa.gov/psd/data/timeseries/AMO/. Timeseries are calculated from the Kaplan SST dataset (Kaplan et al. 1998)

is an anomalous low over North America, the subtropical North Atlantic, and over the eastern subtropical Pacific. During the cold phase, the pattern shows an anomalous low over North America, with a high-pressure anomaly over the eastern subtropical Pacific and subtropical North Atlantic. A schematic diagram (adapted from Hu et al. 2011) is shown in Fig. 17.7. This modification of the pressure pattern due to the AMO is one of the mechanisms leading to climatic shifts in precipitation over Florida on multi-decadal timescales.

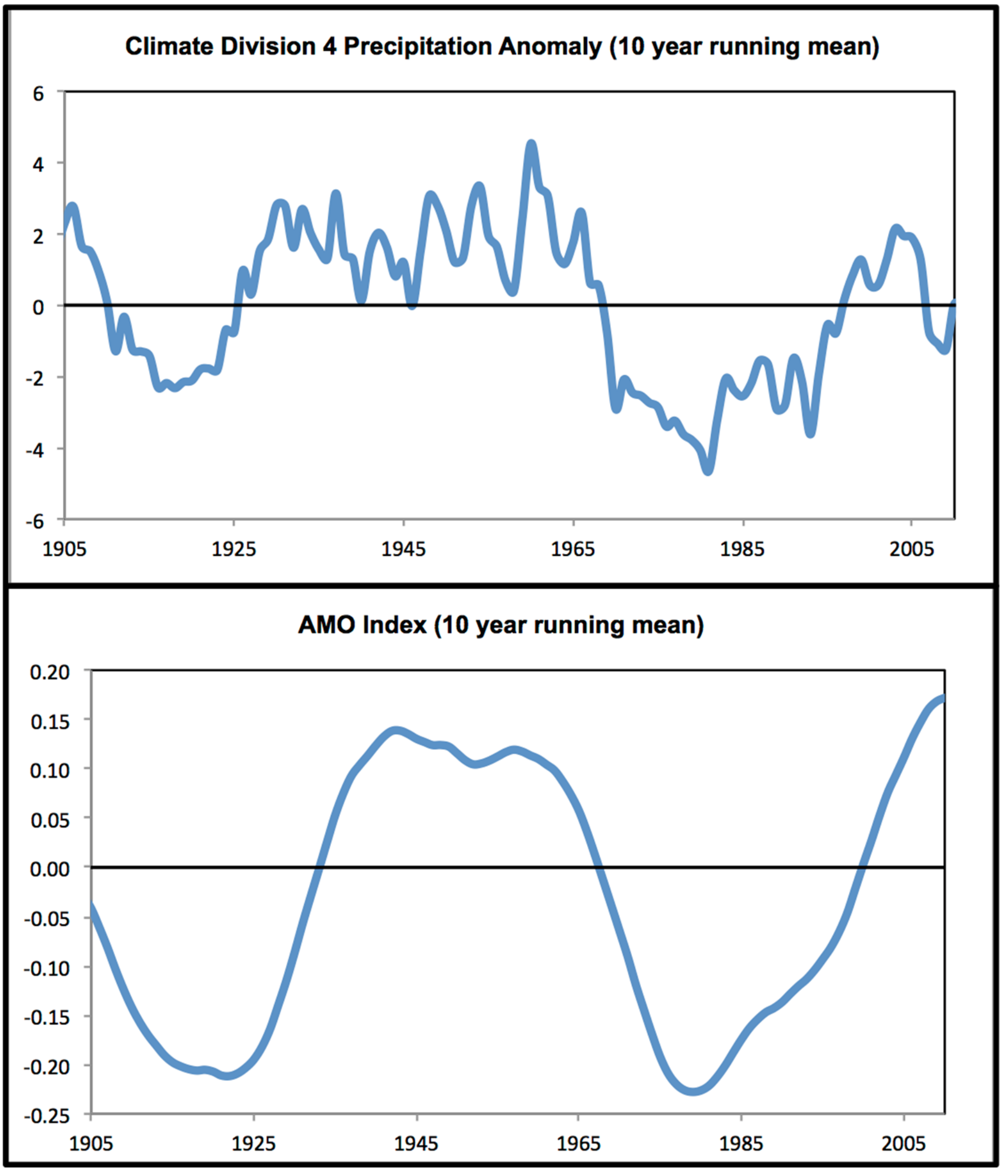

Fig. 17.6. Florida Division 4 rainfall anomalies (10-year running mean) and the AMO index from 1905 to 2010, adapted from (Enfield et al. 2001). The 10-year running mean is defined as the period from 1891–1905 (for example), and this 10-year period is defined at 1905.

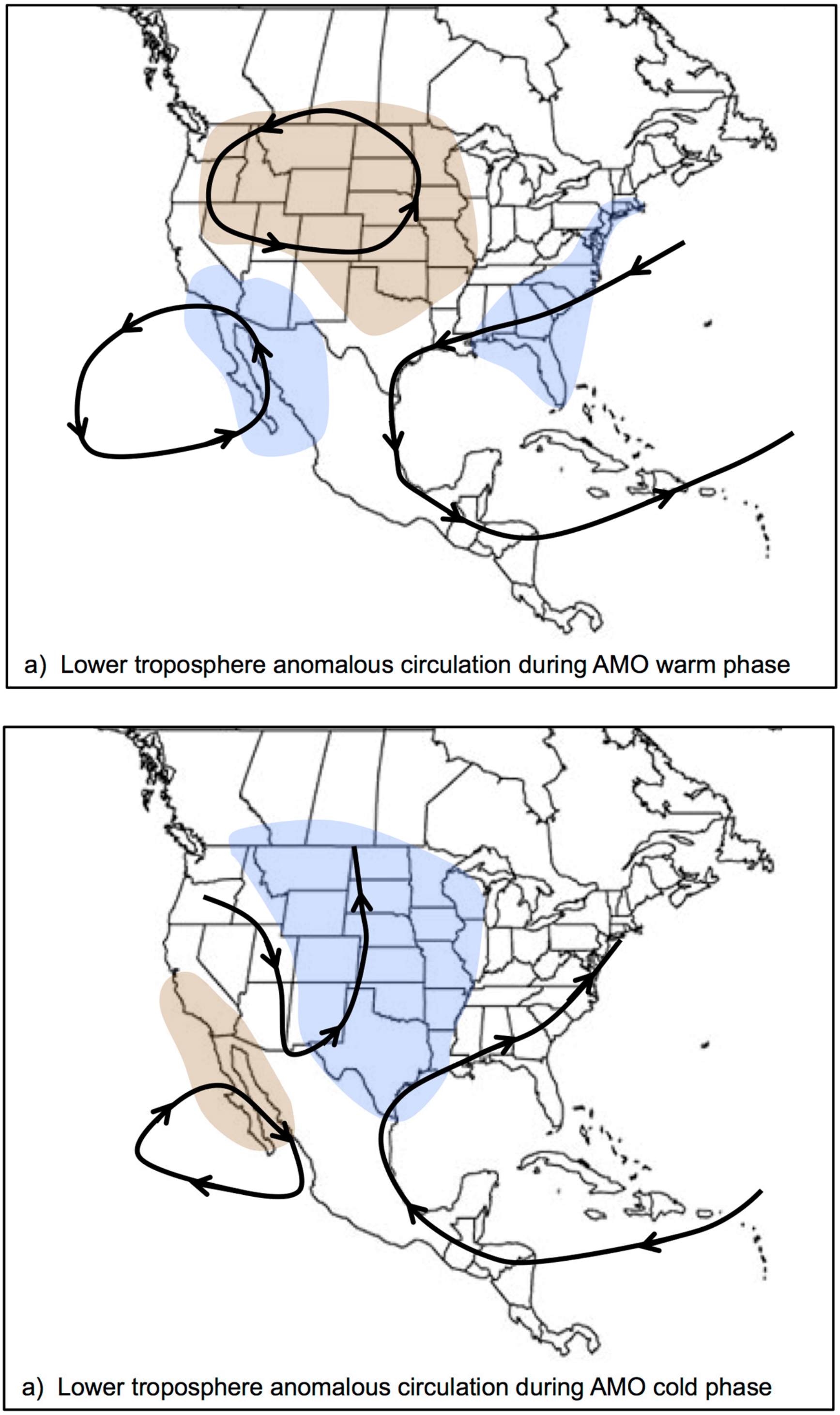

Figure 17.7. A schematic summary of pressure and flow anomalies in the lower troposphere during AMO phases, as well as the expected summer (JJA) precipitation anomalies. This schematic is adapted from Hu et al. (2011) and is an *approximate* representation.

Sources and Mechanisms for Florida Climate Prediction: Why We Can Predict

The discussion above of ENSO, PDO, and AMO emphasizes the physical phenomena leading to global climate variability and the regional impacts over Florida. Why do these phenomena provide the scientific basis for climate prediction? Certainly, a large part of the answer to this question is persistence, particularly for the lower frequency decadal modes of variability. Persistence can be understood by imagining the following scenario. Suppose there is a strong warm ENSO event today. We know that the SST anomalies associated with this warm event will remain in place or *persist* for several weeks – hence persistence. Similarly, if the PDO is in the anomalously warm state for several years, we expect increased chances of enhanced rainfall over Florida. Essentially, there is substantial predictive information in persistence, and this is quite useful. For the higher frequency modes such as ENSO it is necessary to predict the evolution or life cycle and this requires capturing the complex physical interactions and feedbacks that are the underlying mechanism for their existence. Again, using our example of ENSO, the life cycle of individual events is governed by air–sea interactions in the Tropical Pacific and the thermal inertia associated with temperature anomalies in the upper 400 m of the ocean. As the life cycle of ENSO progresses, SSTs in the Pacific shift, driving associated local shifts in rainfall that, in turn, disrupt atmosphere circulation patterns and storm tracks leading to climate variability in remote regions such as Florida. Predicting this life cycle is complex, and the remote impact is influenced by interactions and interference with other modes of climate variability, such as the PDO as discussed earlier.

The regional prediction is further complicated by local climatic interactions and feedback. For instance, suppose that the soil over a large region of Florida is anomalously wet. Soil moisture or soil water content has significant inertia or memory. This means that the wet conditions would persist for several weeks, leading to enhanced evaporation during this period. This enhanced evaporation leads to cooling of the surface temperatures and potential moistening the atmospheric boundary layer, which then leads to changes in local circulation and rainfall. Similar local interactions can also occur with SSTAs in the nearby oceans. Ultimately, useful predictions will need to include the effects of all large-scale climate drivers, the local impact of these drivers, as well as local climatic feedbacks and interactions. Indeed, the regional prediction challenge is daunting.

Tools for Predicting Near-Time Florida Climate Variability

The fundamental building blocks of any prediction system include: (a) observational data and observing networks, (b) systems for assimilating or filling in gaps in the observational estimates, and (c) statistical or (semi-) empirical models and/or dynamical models (e.g., computer models primarily based on governing physical laws). These building blocks are also intimately connected. For example, the development of statistical models strongly depends on the robustness of our observing networks, and the fidelity of data assimilation systems are often affected by the quality of dynamical computer models. Moreover, the design of observing networks is based on our understanding of the physical phenomenon, which is in part based on our dynamical and statistical models. The intent of the section is to briefly summarize the basic tools for predicting Florida climate variability and describe their current capabilities. A more detailed discussion on the strengths and limitations of prediction systems can be found in NRC 2010 (National Research Council 2010).

Observational estimates are essential as they: form the basis of our physical and dynamical understanding of climate system; are used to derive empirical/statistical models; are the basis of the "initial condition" of any statistical or dynamical prediction system; and are used to assess the quality of our prediction systems. Observations are measurements of climatically relevant variables (e.g., SSTs, rainfall, sea level, …) that are made in situ (rain gauge network or ocean buoy) and are also made using remote platforms such as satellites or weather balloons. The development and implementation of global prediction systems require observational estimates of the entire state of the climate system (ocean, land, atmosphere, and cryosphere). This is different from weather prediction, which largely focuses on just the state of the atmosphere (and to some degree the land surface). For example, we know that ENSO and the PDO (see section above) affect Florida rainfall anomalies. To predict the future evolution of ENSO and the PDO, we need observational estimates of the state of the ocean and the atmosphere in the Pacific. Moreover, observations of Florida land surface temperatures and rainfall are needed to understand, initialize, and verify the predictions of the local manifestation of the global drivers (i.e., ENSO and the PDO). The local land surface state is also likely to be important since, for example, soil moisture anomalies can affect the local recycling of rainfall and the persistence of drought, which can either destructively or constructively interfere with the signal from the global climate drivers. Indeed, regional climate prediction is a daunting observational challenge.

Another challenge is that observational estimates rarely come in a form that can be easily adapted for understanding, verifying, or initializing predictions. For example, there are many spatial-temporal gaps in the observational estimates, and techniques are required to fill in these gaps. There are a variety of these techniques with a wide range of complexity and sophistication that are generically referred to as data assimilation. Again, we do not provide an exhaustive discussion of data assimilation here and refer the reader to NRC 2010. Nevertheless, from the perspective of prediction, data assimilation blends observational data and models (either statistical or dynamical) to estimate the entire state of the climate system, and these state estimates are used to initialize predictions and, in some cases, to verify predictions.

The capstone of any prediction system is the dynamical and/or statistical model that is used to take the state of the climate system today (i.e., the initial condition) and evolve it into some estimate of the state of the climate system in the future. The dynamical or computer model-based approach uses the physical laws from geophysical fluid dynamics and thermodynamics, whereas the statistical or empirical models use relationships derived from observational estimates. Both approaches have strengths and weaknesses, and ultimately prediction data that is used to guide decisions about the future is based on a suite of dynamical and statistical tools. The pragmatic use of multiple prediction tools/systems is typically referred to as the multi-model approach, and is currently viewed as the best practice for prediction across various timescales (see Kirtman et al. 2014 for discussion of the utility of the multi-model approach). The current capability of seasonal prediction is summarized in the section below.

Seasonal Prediction

As discussed above, our ability to predict seasonal Florida climate variability is largely due the large-scale drivers associated with the ENSO. Lower frequency phenomena such as the AMO and PDO can interact and interfere with the ENSO signal over Florida, and are important components of decadal prediction. However, since decadal prediction is also largely influenced by climate change associated with changes in atmospheric composition (e.g., CO_2, methane, aerosols), these decadal modes are discussed in more detail in the next chapter. The interested reader is referred to Kirtman et al. (2013) for a complete discussion of the issues and challenges associated with prediction over timescales from weeks to decades. Here, we focus on current capabilities in seasonal prediction with an emphasis on Florida. We begin with a brief description of the North American Multi-Model (NMME; Kirtman et al. 2014; www.cpc.noaa.gov/products/NMME), which is an official NOAA operational product and an excellent example of the current state-of-the-art in real-time/operational prediction. However, we also use the NMME as an example of one of the grand challenges in regional seasonal prediction, namely, how to make predictions with sufficient regional spatial-temporal resolution as to be useful for decision support.

The North American Multi-Model Ensemble Prediction System

Weather and climate forecasts are necessarily uncertain, and if the forecasts are to be used for effective risk assessment and decision support this uncertainty must be quantified. In terms of global prediction systems, the uncertainty or forecast probability distribution is typically estimated by making ensemble predictions with perturbed initial conditions and multiple models (see Kirtman et al. 2014). The use of multiple models or perturbing the physics in a single model serves to probe uncertainty due structural errors in model formulation. The NMME Project is an integrated research and operations partnership specifically designed to ensure that forecast uncertainty is adequately quantified.

The multi-model ensemble approach has proven extremely effective at quantifying prediction uncertainty due to uncertainty in model formulation, and it has proven to produce better prediction quality (on average) than any single model ensemble. There are numerous examples of how this multi-model ensemble (MME) approach yields superior forecasts compared to any single model. For example, Fig. 17.8, which is compiled from the NMME project data, compares the Ranked Probability Skill Score (RPSS) of the Climate Forecast System version 2 (CFSv2) (right panel; single NOAA operational model) to the grand NMME ensemble (left panel) for the DJF precipitation forecast for North America at six months lead. Details of how RPSS is calculated are omitted here; the important point to note is that larger values correspond to more useful information that can be translated into economic value. In terms of interpreting the results in Fig. 17.8, it is clear that the RPSS is larger for the MME compared to the single model. This improvement is particularly notable for Florida.

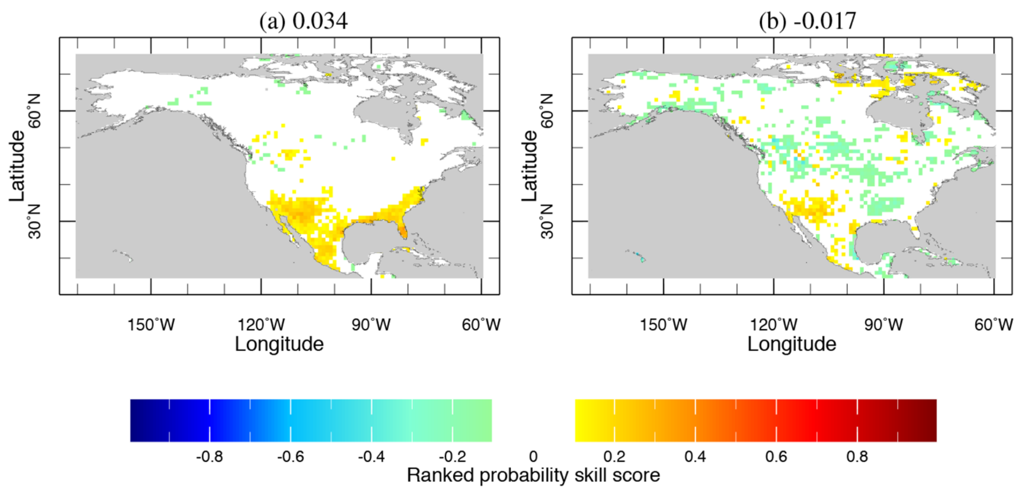

Figure 17.8. Precipitation forecast Rank Probability Skill Scores (RPSS) for the grand NMME (left panel) and for CFSv2 (right panel; single NOAA operational model). The skill is based on hindcasts initialized in July 1982-2010 and verifying the following DJF seasonal mean for tercile forecasts. Positive values indicate probabilistic skill that is better than climatology, and negative values indicate probabilistic skill that is worse than a climatological forecast. Area average RPSS is noted in the figure.

An example of a real-time operational North American rainfall anomaly forecast from the NMME project is presented in Fig. 17.9. The probability forecast indicates a 40-50% chance of below normal rainfall, allowing for the possibility (i.e. uncertainty) of near normal or even above normal rainfall throughout most of the southern tier of the US including Florida. The forecast also indicates a fairly strong probability of above normal rainfall in the northern tier of the US. Note that probability forecasts can be refined for different categories (e.g., quintiles) or even thresholds of exceedance. Finally, experimental CCSM4 forecasts with a regional southeast US focus are available at (http://benkirtman.weebly.com/climate-forecasts.html). CCSM4 is one of the many climate models included in the NMME suite.

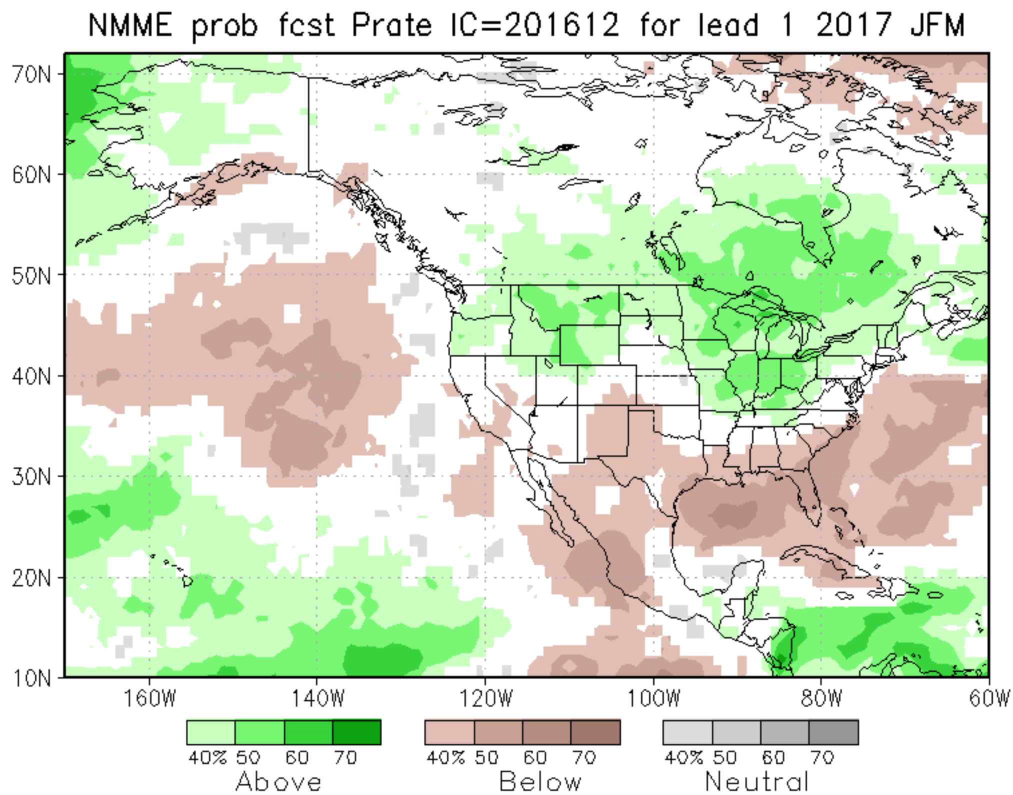

Figure 17.9. Example of NMME real-time operational rainfall forecast initialized 1 December 2017 and valid for January-February-March 2017 (JFM2017).

Regional Florida Prediction: Statistical Downscaling

The increased desire for localized climate prediction and projections makes the raw output from current global climate models, which are comparatively coarse in spatial resolution, inadequate (Giorgi et al. 2009). In order to overcome this limitation, various techniques for regionalization or downscaling of global model analyses or predictions have been adopted. These methods have been traditionally classified as either statistical or dynamical downscaling(Wilby and Wigley 1997). Although many different statistical downscaling tools exist (e.g. Wilby et al. 2004), they all essentially seek to relate the regional- tolocal-scale predictands with large-scale predictors (Hewitson and Crane 1996). Dynamic downscaling techniques use numerical climate models restricted to a regional domain of interest and forced at the lateral boundaries of the regional domain by the coarser global model or analysis (Warner et al. 1997). There is no clear consensus on one method being superior to the other (Wilby and Wigley 1997), although the statistical downscaling approach is far less computationally intensive than the dynamic downscaling approach. However, one of the two approaches may be more appropriate than the other for a particular region or end-use. For instance, the statistical downscaling approach may be less suitable in regions with unreliable historical local climate data or where the local climate data may have an insignificant relationship with large-scale climate variations. Similarly, dynamic downscaling may be inefficient where statistical approaches provide reliable predictions or projections, or where the intent is not to downscale the full 4-D (three dimensions of space and time) of the local climate.

Statistical Downscaling

For regional decision support, the resolution of the NMME global forecasts is far too coarse for direct use by, for example, water resource managers or to drive decision support models used for extreme sea states. Work adopted from Tian et al. (2014) illustrates an example of the spatial resolution challenge in downscaling the NMME data to the National Land Data Assimilation System phase 2 (NLDAS-2) grid (0.125x0.125; Fig. 17.10). Better tools are required in order to provide environmental predictions on spatial scales of a few kilometers. However, this need for better tools introduces another source of uncertainty that is inadequately evaluated. For instance, a common approach is to downscale global predictions by "forcing" a regional model with the large-scale information from the global models. This introduces the need to quantify the uncertainty in the large-scale forcing that comes from initial conditions and model formulation.

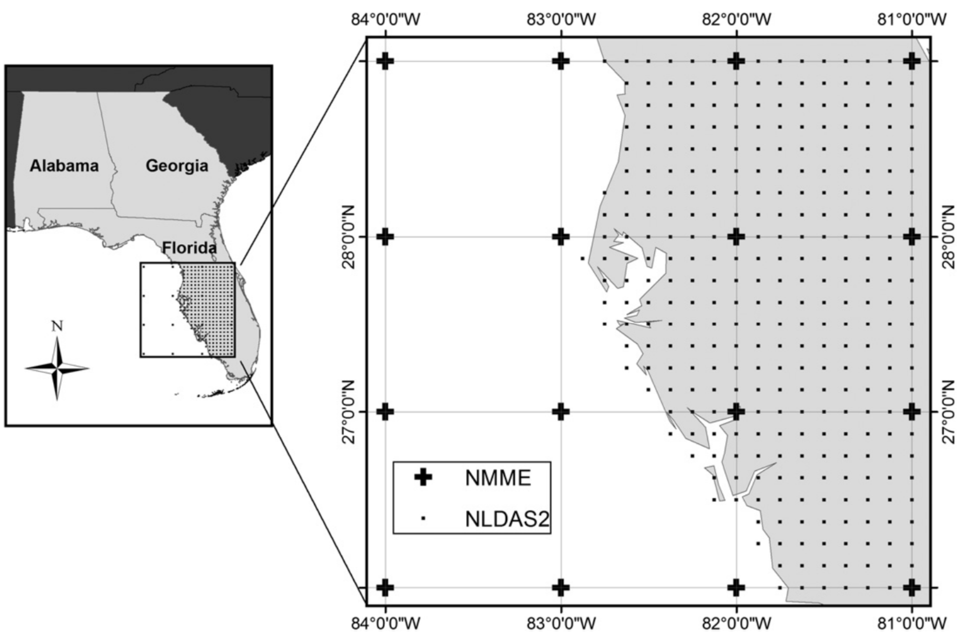

Figure 17.10. Example of large-scale NMME data to be downscaled to fine mesh for Regional Spectral Model (RSM) and other applications (Tian et al. 2014).

There are a number of statistical techniques for disaggregating or downscaling global-scale models such as those used in the NMME projects. Here, we briefly show results described in Tian et al. (2014); that is, (i) using quantile mapping on direct spatial disaggregation and bias correction of the NMME forecast, and (ii) the perfect prognosis approach using nonparametric locally weighted polynomial regression. Fig. 17.11 shows an example comparing skill scores for a one-month lead precipitation forecast for DJF using the two techniques from Tian et al. (2014). The skill scores used in Fig. 17.11 are the Mean Square Error Skill Score (MSESS) and the Brier skill score (BSS). Clearly, the disaggregation has more spatial heterogeneity than is possible when using the NMME forecast without the statistical downscaling.

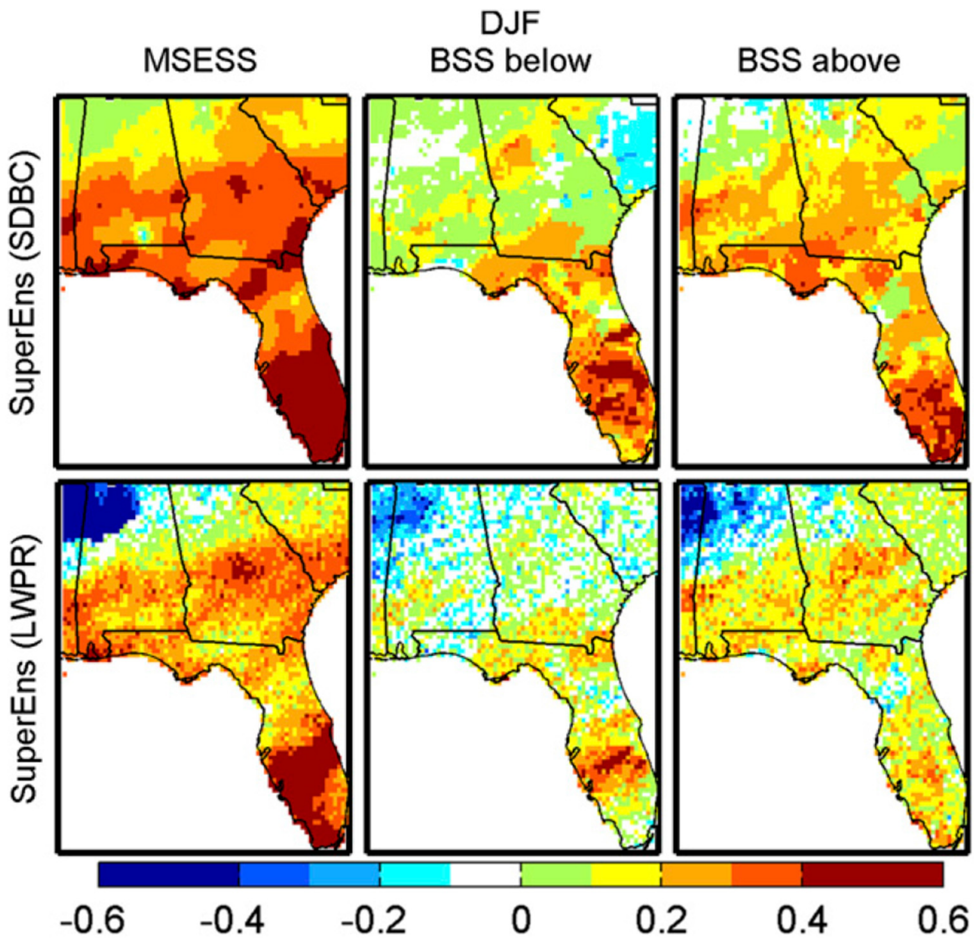

Figure 17.11. Precipitation forecast skill scores (MSESS, BSS) for one-month lead NMME seasonal forecasts downscaled using quantile mapping on direct spatial disaggregation and bias corrected forecast (top row) and nonparametric locally weighted polynomial regression (bottom row). Warm colors indicate skill above climatology whereas cold colors indicate skill worse than climatology. Figure adapted from Tian et al. (2014).

Dynamical Downscaling

The geography of Florida underscores the need for downscaling, as its peninsular structure is barely resolved in many of the current global climate models (Misra and Obeysekera 2011). Furthermore, the robust seasonal cycle of rainfall (Misra and DiNapoli 2013) and the significant contributions to Florida's hydroclimate from mesoscale events (ranging in spatial scales of 10-1000 km and temporal scales of one hour to a day) such as landfalling tropical cyclones (Knight and Davis 2009; Maxwell et al. 2012, 2013; Prat and Nelson 2013 a, b) and diurnal variations emanating from seabreeze thunderstorms (Misra et al. 2011b; Bastola and Misra 2013; Selman et al. 2013; Selman and Misra 2015) call for high resolution models to resolve these processes. Fig. 17.12 is a good illustration of dynamic downscaling, showing the accumulated rainfall from all landfalling tropical cyclones in the regional domain between 1948–2000 for El Niño (Figs. 17.12a-c) and La Niña (Figs. 17.12d-f) years. The dynamic downscaling was conducted at 10 km grid spacing from a coarser global reanalysis (Compo et al. 2011), which was at 2.5º (~300 km) grid spacing over a period of 104 years (1901–2004; Misra et al. 2012). The coarser analysis shows an unrealistically smooth distribution of rainfall from landfalling tropical cyclones in El Niño (Fig. 17.12a) and La Niña (Fig. 17.12d) years contrary to the corresponding observed rainfall distribution (Figs. 17.12c and f). The more detailed and inhomogeneous distribution of rainfall is described in the dynamic downscaling approach (Figs. 17.12b and e). There are, however, obvious differences between the observations (Figs. 17.12c and f) and the corresponding dynamic downscaling simulations (Figs. 17.12b and e) that relate to the limitations of the approach, including the use of an imperfect numerical model and the inherent chaotic nature of the regional climate system.

One of the major limitations of the dynamic downscaling approach is that it is significantly influenced by the quality of the coarser model forcing the lateral boundaries of the regional domain (Warner et al. 1997; Misra 2006). In the case of Florida, this becomes a significant issue when all current global climate models display a significant cold bias in the Gulf of Mexico and in the Caribbean Sea (Kozar and Misra 2012), which then translates to a dry bias over Florida (Selman et al. 2013). This cold bias in the global models is attributed to erroneous cloud simulations (Misra et al. 2009) and an erroneous Loop Current system in the Gulf of Mexico and the Caribbean Sea (Misra et al. 2017). The Loop Current system is a mesoscale ocean current system that is inadequately resolved in majority of the current global climate models (Liu et al. 2015).

More recently, Misra and Mishra (2017) used a regional coupled ocean–atmosphere model at 10 km grid spacing to downscale a coarser global ocean and atmospheric analysis over Florida in order to show that the SST variations from the variability of the Loop Current also influences the terrestrial summer season rainfall over peninsular Florida. For instance, they show that the systematic weakening of the Loop Current causes the Gulf of Mexico to become colder than normal. As a result, surface evaporation from the cold ocean surface reduces, which essentially results in less moisture for terrestrial convection over the comparatively warm peninsular Florida.

Studies such as Misra and Mishra (2017) show that the dynamic downscaling approach can be feasible for generating reliable predictions or projections for Florida despite an overwhelming display of systematic errors over the surrounding oceans by the current global models.

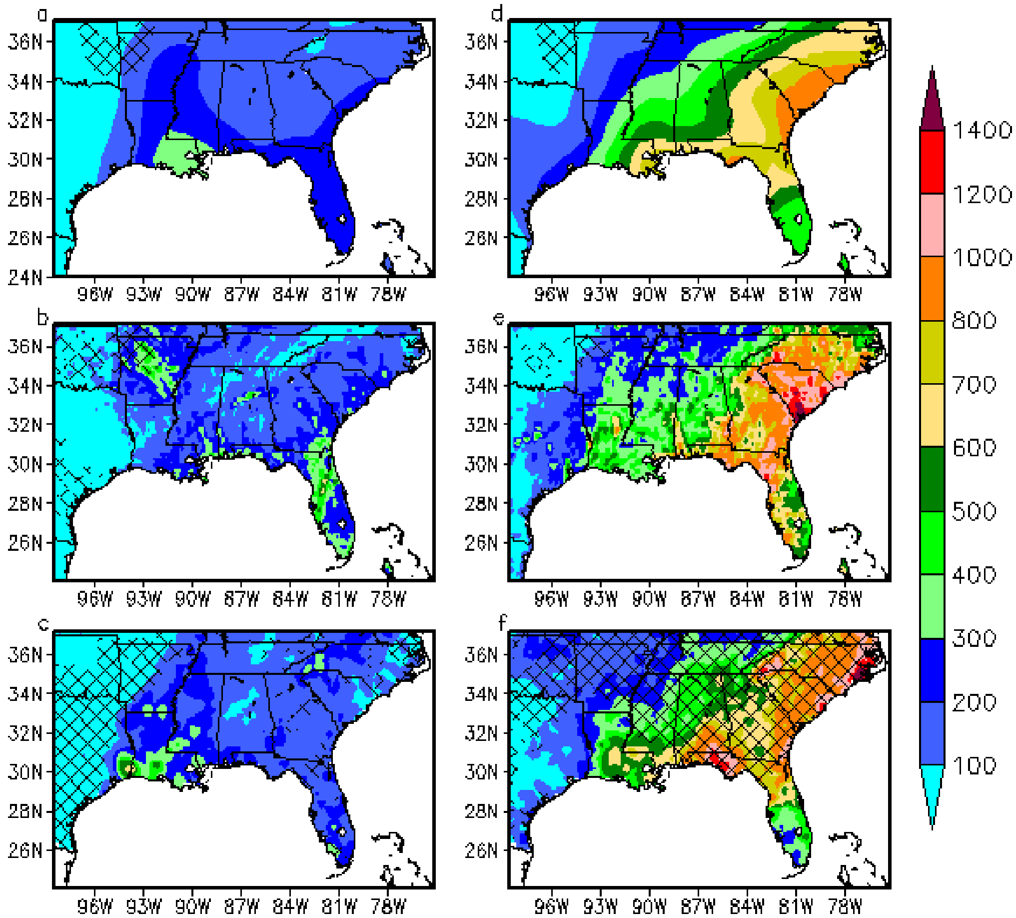

Figure 17.12. The composite rainfall from all landfalling hurricanes in the regional domain shown between 1948–2000 for El Niño years from a) global reanalysis (Compo et al. 2011), b) dynamic downscaling from global reanalysis (Misra et al. 2012), and c) observations (Higgins et al. 2000). Similarly, (d), (e) and (f) are the same as (a), (b), and (c) for La Niña years. The units are mm. The hashes represent statistical significance at 10% significance level from bootstrap method. Adapted from Misra et al. (2012).

Final Remarks

The demand continues to grow for prediction information on times scales of weeks to decades, as –many sectors of society are increasingly vulnerable to climate variability, and robust information saves lives and property. Indeed, there is also compelling evidence that as the climate continues to warm our vulnerabilities will continue to increase and that forecasts on response and adaptation timescales (i.e., weeks to decades) are essential for sustainable and resilient communities. It is also clear that there is much room for improvement in predicting regional climate variability and in using forecasts to inform decisions for societal benefit.

Clearly one of the most pressing challenges is improving regional forecasts. The current state-of-the-science is unclear about the best approach: do we invest in radical improvements to the resolution of global models? Or, do we focus on developing improved regional downscaling technology? Despite the lack of consensus on the best approach, there remains a pressing need to improve the global models and the regional downscaling techniques. This requires sustained efforts to enhance all of the building blocks of prediction systems (i.e., observations, data assimilation, and models).

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