CHAPTER 18

Future Climate Change Scenarios for Florida

Ben P. Kirtman[1], Vasubandhu Misra[2], Aavudai Anandhi[3], Diane Palko[1], and Johnna Infanti[4]

[1]Rosenstiel School of Marine & Atmospheric Science, University of Miami, Miami, FL; [2]Florida Climate Institute/Center for Ocean-Atmospheric Prediction Studies/Department of Earth, Ocean and Atmospheric Science, Florida State University, Tallahassee, FL; [3]Biological and Agricultural Systems Engineering, Florida Agricultural and Mechanical University, Tallahassee, FL; [4]University Corporation for Atmospheric Research/Florida Atlantic University/University of Miami/United States Geological Survey

This chapter describes both the nature of and anthropogenic mechanisms for climate change, as well as how scenarios and projections of future climate change are made. Specific emphasis is placed on understanding the changes over the near-term (i.e., adaption timescale) where the emission scenario has little impact vs. changes beyond the mid-century where the projections are conditional on the emission scenario. The various tools and models used to assess climate change are also summarized, and projections from global and regional models are presented. Finally, the new science of decadal prediction is presented as it has the potential to improve climate information in the near-term.

Key Messages

- The climate science community clearly understand that adaptation decision support needs robust regional information, and that the current generation of global models are not sufficient in this regard.
- Efforts to downscale the global models are promising but much remains to be done.

Keywords

Anthropogenically forced climate change; Decadal climate prediction; Climate projection; Climate scenario; Mitigation; Adaptation

Terminology and Definitions

The language of climate change and climate variability can often be confusing. In this section, we introduce terminology applicable to this chapter. The intent here is to clarify and simplify the discussion–we make no claim that this terminology list is complete, exhaustive, or universally excepted. Much of the discussion follows chapter 11 of the 2013 Intergovernmental Panel on Climate Change report (i.e., Kirtman et al. 2013). The important terms are first introduced in italic font.

Internally Generated vs. Externally Forced Climate Variability

The terms *climate change* and *climate variability* are typically used rather loosely. It is, perhaps, more well-defined to use the terms *externally forced climate variability* and *internally generated climate variability*. Externally forced climate variability (in the vernacular of climate change) describes how the climate system responds to changes in external forcing whether they be natural (e.g., changes in solar output, volcanoes, natural methane from permafrost melt, dust, continental drift) or anthropogenic, that is due to human activities (e.g., CO_2 concentrations from fossil fuel emissions, methane from natural gas production, land use and land cover change). Some confusion arises when it is unclear whether the externally forced climate variability is natural or anthropogenic. Throughout this chapter, we attempt to be clear about which type of variability we are referring to.

Internally generated climate variability (in the vernacular of climate variability) refers to the natural climate variability that would happen if all forcing (natural and anthropogenic) was fixed or unchanging. For example, the modes of climate variability discussed in Chapter 17 of this book —including the El Niño–Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), and the Atlantic Multidecadal Oscillation (AMO), among others—would occur without changes in the external forcing of the climate system. These modes are natural elements of the climate system that typically are due to interactions among the components of the climate systems (i.e., land–surface, sea–ice, ocean, and atmosphere). However, even though this internally generated climate variability exists without any changes in the external forcing, we cannot assume that changes in external forcing will not affect these natural modes. Indeed, the effect of increasing CO_2 levels on ENSO remains an active area of research, and remains very much an open science question.

Climate Prediction, Projection and Simulation, Scenario

There is also a distinction between a *climate projection* and a *climate prediction*. A climate projection is a statement about the future of the climate system that is conditional on the changes in the external forcing. For example, one might ask what is the state of the climate system 100 years from now if we assume CO_2 will increase by 1% per year or 2 % per year? The response would be very different if the *scenario* is a 1% vs. 2% per year increase. The science of climate projection, therefore, is highly dependent on the specific future scenario for the anthropogenic external forcing. In the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), these scenarios are referred to as Representative Pathway Concentrations (RCPs) and are typically formulated by economic assumptions since, for example, CO_2 emissions are well correlated with gross domestic production.

In contrast, a climate prediction is conditional on the external forcing and the initial condition (see Chapter 17 for a more detailed discussion of this). Simply put, a climate prediction attempts to capture the evolution of the natural modes of variability and, at the same time, the response to the changes in the external forcing. For the *seasonal predictions* discussed in Chapter 17, the initial condition is of paramount importance and the external forcing is relatively unimportant. For longer timescale prediction such as decadal both the initial condition and the evolving external forcing are important. When the timescales of interest are even longer (i.e., greater than say 20–30 years), then the initial condition is of much smaller importance and the external forcing is paramount. At very long timescales (i.e., beyond 30 years), for all practical purposes and assuming the same external forcing scenario, climate projection and climate prediction are indistinguishable. On the other hand, assuming the same external forcing scenario a ten-year prediction and projection may be very different.

We also need to make the distinction between a climate projection and a *climate simulation*. Much like a climate projection, a climate simulation is a computer model-based depiction of the evolution of a climate system conditional on the historical or past-observed external forcing. The projection is conditional on the assumed or projected external forcing into the future. Sometimes climate simulations are referred to as historical runs or historical simulations. Fig. 18.1, for example, shows an ensemble of climate simulations (gray curves). Each ensemble member or individual simulation was started with slightly different initial conditions and/or different models so that each simulation has different internally generated climate variability. However, all the ensemble members have the same externally prescribed forcing, so that the ensemble mean or average of all the ensemble members across all models is an estimate of the observed (black curve) externally forced climate over the past. The climate simulation can simply transition into a projection as the external forcing evolves into an assumed future evolution (various colored curves or the RCPs).

A *scenario* is a coherent and plausible description of a possible future state of the world. Scenarios are not projections or predictions, neither predicting nor forecasting future conditions. They differ from forecasts, which impose patterns extrapolated from the past onto the future. Since climate scenarios envisage assessment of future developments in complex systems, they are often inherently unpredictable, insufficiently assessed, and have high scientific uncertainties. The climate scenario differs from *climate projection* in that it refers to a description of the response of the climate system to a scenario of greenhouse gas and aerosol emissions, as simulated by a climate model. Climate projections alone rarely provide sufficient information to estimate future impacts of climate change because the model outputs commonly have to be manipulated and combined with observed climate data to be usable, for example, as inputs to impact models. Similarly, a *climate scenario* and a *climate change scenario* are also different, as the term climate change scenario refers to a representation of the difference of some plausible future climate from the current climate or a control climate, adapted from a climate model (IPCC 2001). A climate change scenario can be viewed as an interim step towards constructing a climate scenario because a climate scenario requires combining the climate change scenario with the observed current climate.

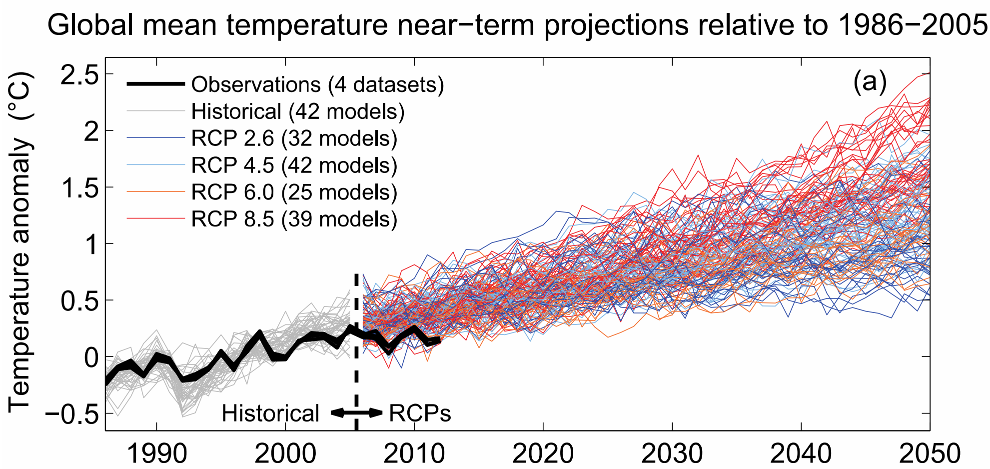

Figure 18.1. Climate simulations and projections of annual mean global mean surface temperature 1986–2050 (anomalies relative to 1986–2005). Projections under all RCPs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) models (grey and colored lines, one ensemble member per model), with four observational estimates for the period 1986–2012 (black lines). Figure taken from Kirtman et al. (2013).

Near-Term vs. Long-Term Climate

In part driven by the distinction between climate projection and climate prediction, we also make the distinction between *near-term* climate and *long-term* climate. Near-term refers to the period from the present day to the mid-century and long-term refers to the period from the mid-century until 2100 and perhaps beyond. This distinction is useful from at least three specific perspectives. First, in the near-term the response to plausible differences in external forcing scenarios are relatively small. To be clear, the evolution of external forcing remains very important. We are simply acknowledging that any differences between plausible scenarios does not emerge until about the mid-century. Essentially, over the next 20–30 years or so, we have already committed to a certain amount of climate variability (i.e., warming) due to past anthropogenic external forcing. An example of this relative insensitivity to external forcing scenario and the increases in the global mean surface air temperature projections are shown in Fig. 18.2. Differences in the global mean surface temperature projections do not become significant until about the mid-century.

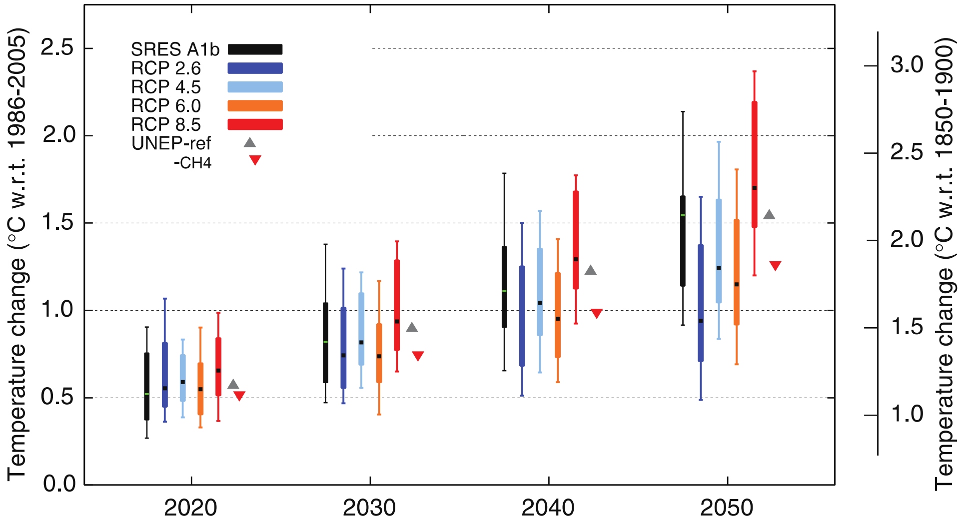

Figure 18.2. Near-term increase in global mean surface air temperatures (°C) across scenarios. Increases in 10-year mean (2016–2025, 2026–2035, 2036–2045 and 2046–2055) relative to the reference period (1986–2005) of the globally-averaged surface air temperatures. Results are shown for the CMIP5 model ensembles for RCP2.6 (dark blue), RCP4.5 (light blue), RCP6.0 (orange), and RCP8.5 (red) and the CMIP3 model ensemble (22 models) for SRES A1b (black). The multi-model median (square), 17 to 83% range (wide boxes), 5 to 95% range (whiskers) across all models are shown for each decade and scenario. Also shown are best estimates for a UNEP scenario (UNEP-ref, grey upward triangles) and one that implements technological controls on methane emissions (UNEP CH4, red downward-pointing triangles) (UNEP and WMO 2011; Shindell et al. 2012). Both UNEP scenarios are adjusted to reflect the 1986–2005 reference period. The right-hand floating axis shows increases in global mean surface air temperature relative to the early instrumental period (0.61 °C), defined from the difference between 1850–1900 and 1986–2005 in the Hadley Centre/Climate Research Unit gridded surface temperature data set 4 (HadCRUT4) global mean temperature analysis. Note that uncertainty remains on how to match the 1986–2005 reference period in observations with that in CMIP5 results. Figure from Kirtman et al. (2013).

Second, we want to make the distinction between *adaption* and *mitigation* in the context of near-term and long-term climate. This distinction is fairly straightforward since adaptation focuses on how ecosystems (including human activities) respond to both internally generated and externally forced climate variability. Adaptation is defined as 'adjustment in ecosystem management in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities' (Anandhi 2017). There are three levels of adaptation, depending on the degree of change and the benefits of adaptation: 1) Incremental adaptation refers to changes in practices and technologies within an existing system. These are tactical choices requiring minimal financial investment, few cropping seasons for the mastery of associated managerial skills, and they can be reversed from one cropping season to another. 2) Systems adaptation are changes to an existing system, such as new crop types that are mapped against an increasing degree of change. 3) Transformational adaptation refers to the more radical end of a spectrum of change, such as a change inland use. Adaptations become systemic and then transformational in proportion to their irreversibility, capital requirements, life time, and impact

(Anandhi 2017). These are discussed in detail in Chapter 8. Adaptation is typically a near-term issue since we have already committed to a certain level of warming, and ecosystems will necessarily have to respond. Mitigation is about reducing or modifying external anthropogenic forcing either through reducing greenhouse gas emissions or through some sort of geoengineering solution to enhance to sinks of greenhouse gases (e.g., scrubbing CO_2 from the atmosphere). This is more of a long-term issue since the changes in external forcing or the emergence of a geoengineering solution will mostly affect long-term climate. Third, we noted above that decadal climate prediction is at the boundary where both initial condition and external forcing are important. Therefore, decadal climate prediction is primarily a near-term climate problem that is potentially useful for adaptation, whereas climate projections that reach 2100 are more aptly used for mitigation.

Criteria for Selection of Climate Scenario

Not all imaginable futures can be viable scenarios of future climate. The suitability of each type of scenario for use in policy-relevant impact assessments can be evaluated based on the following five criteria (Mearns et al. 2001; Anandhi 2017):

- Physical plausibility and realism: Changes in climate should be physically plausible, such that changes in different climatic variables are mutually consistent and credible.
- Consistency at regional level with global projections: Scenario changes in regional climate may lie outside the range of global mean changes but should be consistent with the theory and model-based results.
- Appropriateness of information for impact assessment: Scenarios should present climate changes at an appropriate temporal and spatial scale, for a sufficient number of variables, and over an adequate time horizon to facilitate impact assessment.
- Representativeness of regional climate: Scenarios should represent the potential range of future regional climate change.
- Accessibility: The information required for developing climate scenarios should be readily available and easily accessible.

Types of Scenarios

Four types of climate scenarios have been adapted in impact assessments (Mearns et al. 2001; Anandhi 2007), namely: incremental scenarios, analogue scenarios, a general category of "other scenarios," and scenarios based on the outputs from climate models. The most commonly used scenario type is based on outputs from climate models. The other three types have usually been applied with reference to or in conjunction with model-based scenarios.

- **Incremental scenarios** describe techniques where particular climatic (or related) elements are changed incrementally by arbitrary amounts (e.g., +1, +2, +3, +4°C change in temperature). These scenarios are also referred to as synthetic scenarios (IPCC 1994), as they do not necessarily present a realistic set of changes that are physically plausible. They are usually adapted for exploring system sensitivity prior to the application of more credible, model-based scenarios (Anandhi et al. 2016).

- **Analogue scenarios** are constructed by identifying recorded climate regimes, which may resemble the future climate in a given region. Both spatial and temporal analogues have been used in constructing climate scenarios.
    - **Spatial analogues** are regions which currently have a climate analogous to that anticipated in the study region in the future. For example, using a region in Africa as a spatial analogue for the potential future climate over South Florida.
        - **Temporal analogues** make use of climatic information from the past as an analogue for possible future climate. They are of two types: palaeoclimatic analogues and instrumentally based analogues. Palaeoclimatic analogues are based on reconstruction of past climate periods from fossil evidence, such as plant or animal remains and sedimentary deposits. Examples of past periods are the mid-Holocene and the Last (Eemian) Interglacial. Periods of observed global scale warmth during the historical period have also been used as analogues of a greenhouse gas induced warmer world (instrumentally based analogues).
- **Scenarios Based on Outputs from Climate Models:** Climate models at different spatial scales and levels of complexity provide a major source of information for constructing scenarios. General circulation models (GCMs), regional climate models (RCMs), and a hierarchy of simple models produce information at the global scale.
    - **Scenarios from simple climate models:** As these models are seldom able to represent the non-linearities of some processes that can be captured by more complex models, the outputs from these models have been used mostly in conjunction with GCM information to develop scenarios using pattern-scaling techniques.
    - **Scenarios from GCMs:** From the early 1990s, GCM-based scenarios generally refer to outputs from coupled Atmosphere-Ocean GCMs (AOGCMs). AOGCM simulations start by modeling historical forcing by greenhouse gases and aerosols from the late 19th or early 20th century onwards. Climate scenarios based on these simulations are being increasingly adopted in impact studies along with scenarios based on ensemble simulations and scenarios accounting for multi-decadal natural climatic variability. There are several limitations that restrict the usefulness of these outputs for impact assessment: (1) their coarse spatial resolution compared to the scale of many impact assessments; (2) the difficulty of distinguishing an anthropogenic signal from the noise of inherent internal model variability; and (3) the difference in climate sensitivity between various models. In spite of these limitations, AOGCMs are widely used for developing climate scenarios for quantitative impact assessments.
        - **Downscaled scenarios:** The difficulty encountered in using the scenarios from GCMs has been the mismatch of spatial scales between GCMs and local impact assessments

(Anandhi et al. 2011). To overcome this mismatch, scenarios from GCMs at a global scale are translated to scenarios at regional or local scale using downscaling approaches. Two different downscaling approaches that are currently being pursued are dynamic downscaling and statistical downscaling. In the dynamic downscaling approach a RCM is embedded into GCM. There are two types of dynamic downscaling based on the types of nesting: one way nesting and two way nesting. Statistical downscaling involves developing quantitative relationships between large-scale atmospheric variables (predictors) and local surface variables (predictands). There are three types of statistical downscaling, namely weather types, weather generators, and transfer functions.

- **Other Types of Scenarios** Four additional types of climate scenarios have also been adopted in impact studies.
  - The first type involves extrapolating ongoing trends in climate that have been observed in some regions and that appear to be consistent with model-based projections of climate change. There are obvious dangers in relying on extrapolated trends, because if current trends in climate are pointing strongly in one direction, it may be difficult to defend the credibility of scenarios that posit a trend in the opposite direction, especially over a short projection period.
  - A second type of scenario uses empirical relationship between regional climate and global mean temperature from the instrumental record to extrapolate future regional climate on the basis of projected global or hemispheric mean temperature change. Again, this method relies on the assumption that past relationships between local- and broad-scale climates are applicable to the future conditions.
  - A third type of scenario is based on expert judgment, whereby estimates of future climate change are solicited from climate scientists. The results are sampled to obtain probability density functions of future change. The main criticism of expert judgment is its inherent subjectivity, including problems associated with the likely biases in questionnaire design and in comprehending information gathered from different scientists.
  - A fourth type of scenario is estimated from indicators. An indicator is defined as any variable that represents either the magnitude of an element (e.g., average annual precipitation), the variability of an element (e.g., coefficient of variation for annual precipitation) or the statistical relationship among elements (Anandhi 2017). Indicators are powerful tools to communicate climate change in relatively simple terms by portraying the interrelationships among climate and the ecosystems. They help reveal information on the impacts of climate change in the ecosystems, which can be useful in developing adaptation and mitigation strategies. For example, changes in first fall freeze or last spring freeze in Florida are useful in communicating some changes in climate for specific stakeholders and policy development. The scenarios developed from changes in

freeze are useful in portraying the interrelationships among climate and the citrus or strawberry growers for adapting/mitigating to the changes.

IPCC scenarios

In 1988, the Intergovernmental Panel on Climate Change (IPCC) was jointly established by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP) to assess the scientific, technical, and socio-economic information relevant to the understanding of climate change, its potential impacts, and options for adaptation and mitigation. Since its inception, reports by the IPCC have become the standard works of reference. They are widely used by policymakers, scientists, and other experts for assessing the causes of climate change, its potential impacts, and evolving response strategies. Further, the emission scenarios generated in them are widely used for driving AOGCMs to develop climate change scenarios, and the results are freely available for general use.

In 1992, the IPCC released a set of six global emissions scenarios (IS92a to f), called IS92 scenarios. These scenarios provide estimates of possible occurrences of greenhouse gases based on a wide array of assumptions. Out of the six scenarios, IS92a (also known as the "business as usual" scenario) has been widely adopted by the scientific community during the last decade. The IS92 scenarios were further updated in 2000 and the new set of emissions scenarios that were published in the Special Report on Emissions Scenarios (SRES) (Nakicenovic et al. 2000) are known as SRES scenarios. These SRES scenarios were constructed in a fundamentally different way, with a different range for each projection called a "storyline." There are four storylines (A1, A2, B1, and B2) that describe the way the world population, land use changes, new technologies, energy resources, economies, and political structure may evolve over the next few decades. Recently, four future scenarios' representative concentration pathways (RCPs) (Van Vuuren et al. 2011) have been used. The freely available, state-of-the-art multi-model dataset (multiple GCMs and RCPs) was designed to advance our knowledge of climate variability and climate change.

Near-Term and Long-Term Climate Projections

This section presents dynamical model-based near-term and long-term climate projections. We separate the results into those from the global models reported in the IPCC assessment (Stocker et al. 2013), North American Regional Climate Change Assessment Program (NARCCAP; Mearns et al. 2012), and the archive of statistically downscaled CMIP3 and CMIP5 Climate and Hydrology Projections (DHCP, Brekke et al. 2013).

Multi-Model Climate Projections from Global Models

The figures below (Fig. 18.3 and 18.4) show projections of surface temperature for eastern North America using global multi-model climate projections based on RCP4.5. The top panel shows an area average time series from 1900-2100 for the eastern third of the North America. The grey curves or the historical climate simulations and the colored curves are the results from the climate projections using the various RCPs as noted. The bottom rows show maps of the spatial distribution of the projected change over eastern North America for the near-term (2016–2035), the mid-century (2046–2065) and for the end of the century (2081–2100). The columns indicate, for each point on the map, the 25th, 50th, and 75th percentiles for the multi-model ensemble distribution. The hatching indicates regions where the differences of percentiles are less than the standard deviation of the model-estimated, internally generated present day climate variability. Simply put, the hatching indicates where the projections show little change relative to the present day.

Separate seasonal means for December through February (DJF) and June through July are shown in Figs 18.3 and 18.4. In terms of temperature, these are the extreme seasons and are often of the most interest. Typically, the temperature response is strongest when the background state is coldest; that is, in the higher latitudes and in the cold season (DJF). This is primarily because the land–atmosphere exchange through a comparatively stable atmospheric boundary layer is weaker than in the summer time. Usually in the summer season, the warming of the land surface often leads to increased atmospheric eddies allowing for a more robust exchange of heat and moisture fluxes between land and atmosphere, which moderates the response of land surface temperature to anomalous radiative forcing from increased greenhouse gas emissions. As expected, the temperature response is also largest in the long term. Florida is somewhat in contrast with the rest of eastern North America in that its largest temperature responses are in June through August season.

The rainfall response is presented in Figs. 18.5 and 18.6. In contrast to temperature, the hatched regions are more extensive indicating that the rainfall response does not exceed the internally generated climate variability of the present day. The exception to this is in the far southeast US, and in Florida in particular, where the enhanced dry season rainfall is relatively strong and positive across all timescales. For this emission scenario (RCP4.5), the signal during the wet season over Florida is relatively weak, but indicates small increases (<10%) in rainfall. The larger or stronger emissions scenario (RCP8.5; not shown) indicates a considerably stronger response over Florida in the long term. Interestingly, the multi-model mean in the June-August period at the end of the century with RCP8.5 indicates a 20–30% *reduction* in Florida relative to the present day, whereas the September-November period has a 10–20% increase in rainfall. This seasonal dependence in the differences and in scenario are particularly challenging for planning and responding.

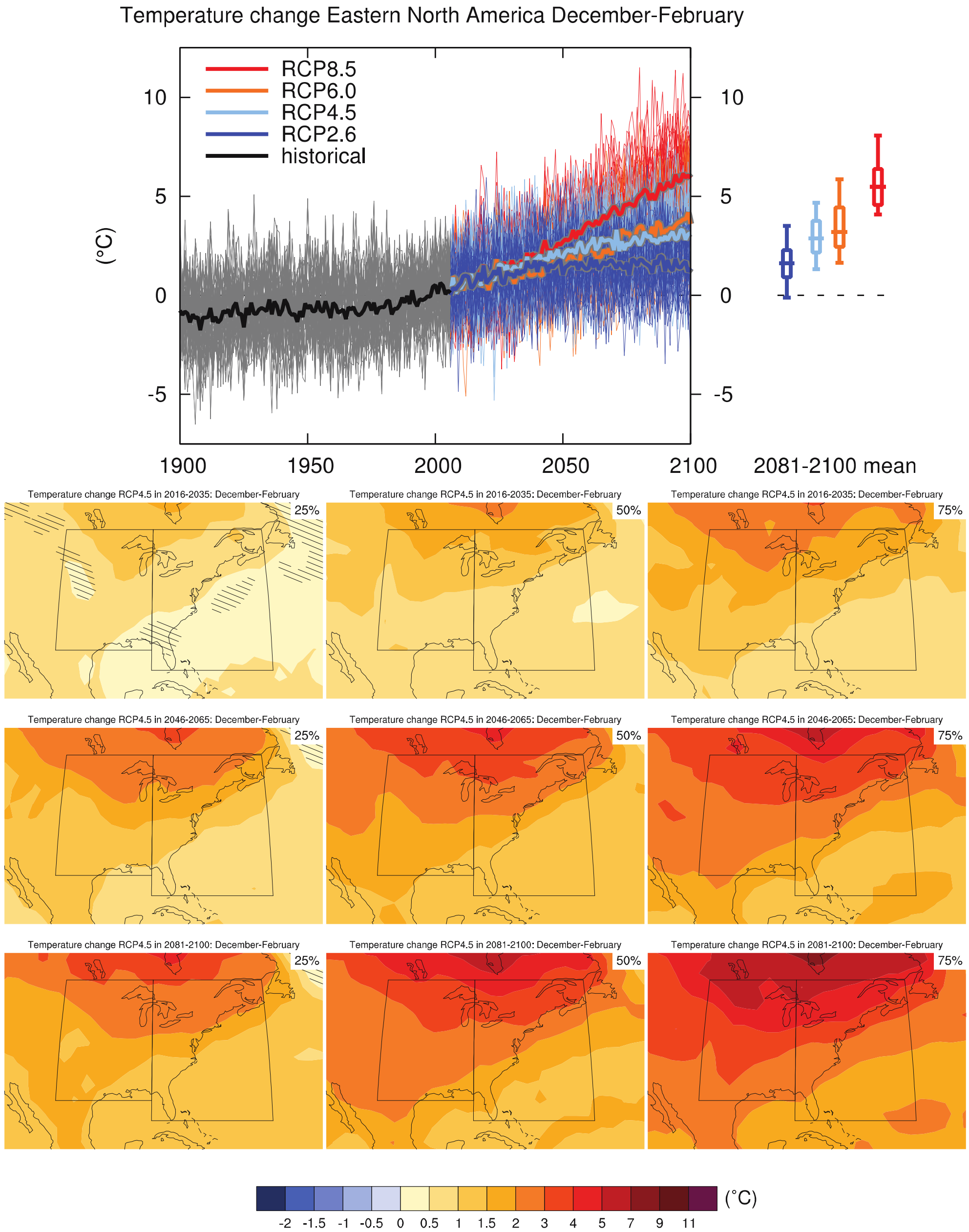

Figure 18.3. Time series of temperature change relative to 1986–2005, averaged over land grid points in eastern North America (25°N to 50°N, 85°W to 60°W) in December to February. Thin lines denote one ensemble member per model, thick lines the CMIP5 multi-model mean. On the right-hand side the 5th, 25th, 50th (median), 75th and 95th percentiles of the distribution of 20-year mean changes are given for 2081–2100 in the four RCP scenarios. (Below) Maps of temperature changes in 2016–2035, 2046–2065 and 2081–2100 with respect to 1986–2005 in the RCP4.5 scenario. For each point, the 25th, 50th and 75th percentiles of the distribution of the CMIP5 ensemble are shown; this includes both natural variability and inter-model spread. Hatching denotes areas where the 20-year mean differences of the percentiles are less than the standard deviation of model-estimated present-day natural variability of 20-year mean differences. Figure from IPCC 2013.

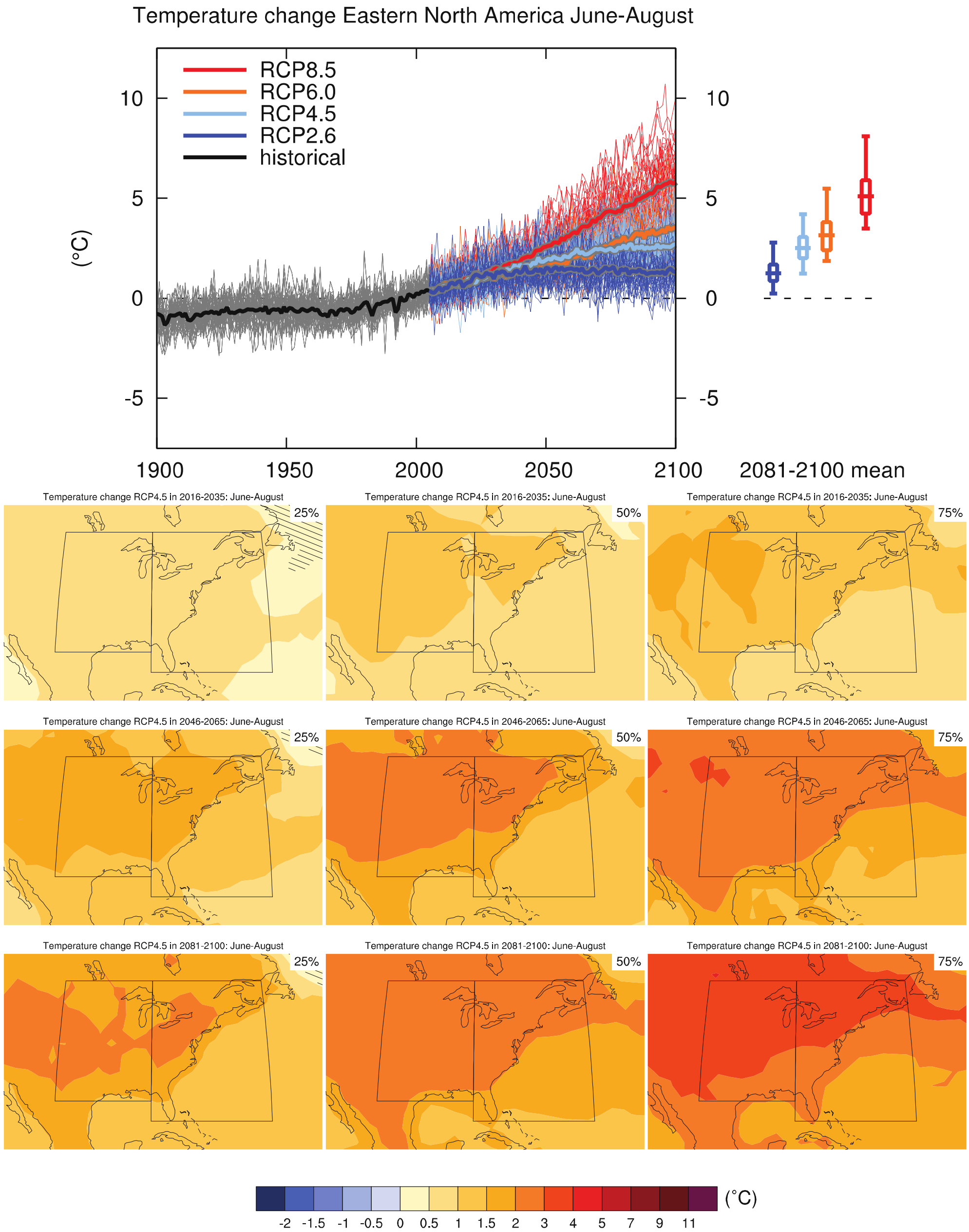

Figure 18.4. Time series of temperature change relative to 1986–2005 averaged over land grid points in eastern North America (25°N to 50°N, 85°W to 60°W) in June to August. Thin lines denote one ensemble member per model, thick lines the CMIP5 multi-model mean. On the right-hand side the 5th, 25th, 50th (median), 75th and 95th percentiles of the distribution of 20-year mean changes are given for 2081–2100 in the four RCP scenarios. (Below) Maps of temperature changes in 2016–2035, 2046–2065 and 2081–2100 with respect to 1986–2005 in the RCP4.5 scenario. For each point, the 25th, 50th and 75th percentiles of the distribution of the CMIP5 ensemble are shown; this includes both natural variability and inter-model spread. Hatching denotes areas where the 20-year mean differences of the percentiles are less than the standard deviation of model-estimated present-day natural variability of 20-year mean differences. Figure from IPCC 2013.

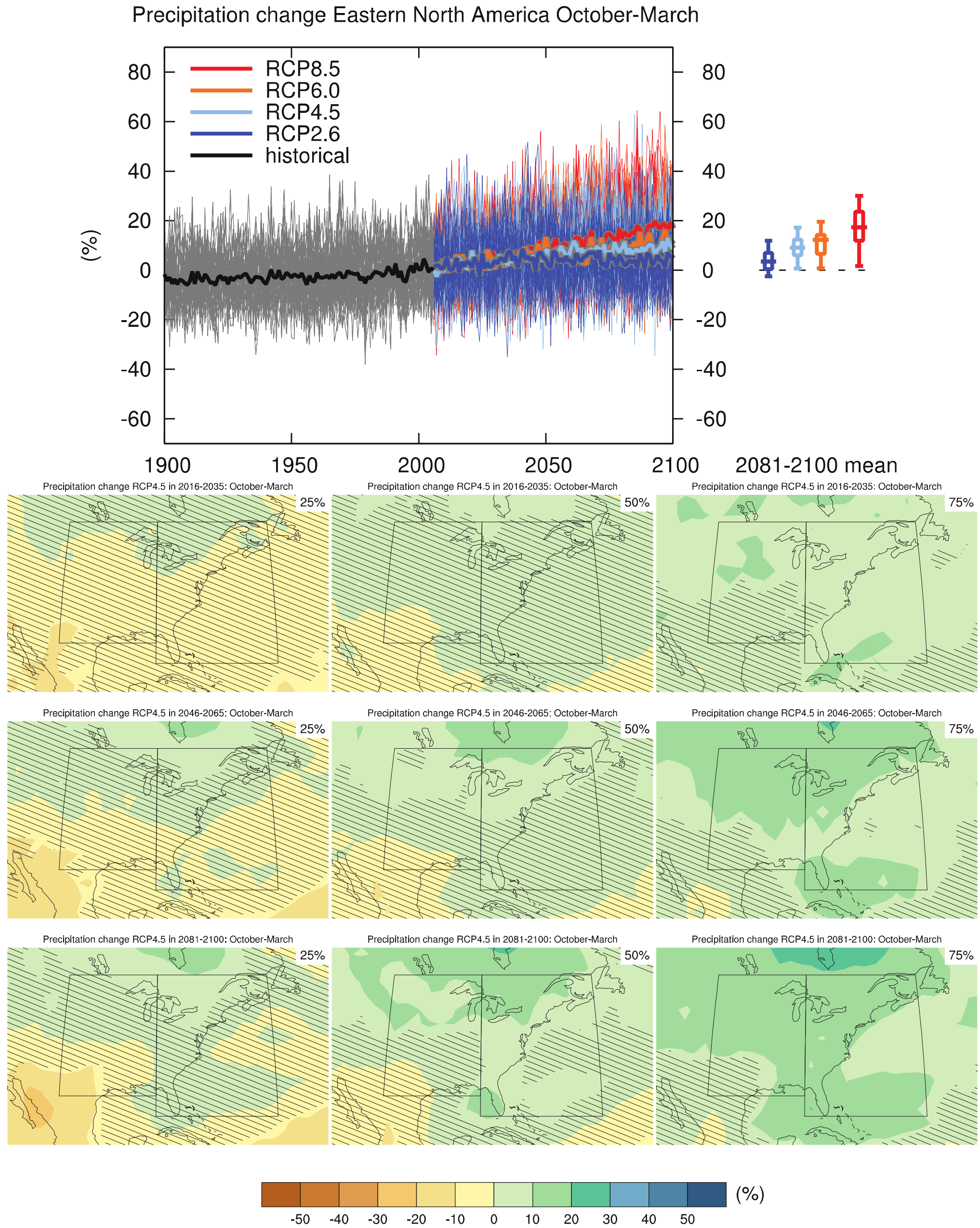

Figure 18.5. (Top) Time series of relative change with reference period 1986–2005 in precipitation averaged over land grid points in Eastern North America (25°N to 50°N, 85°W to 60°W) in October to March. Thin lines denote one ensemble member per model, thick lines the CMIP5 multi-model mean. On the right-hand side the 5th, 25th, 50th (median), 75th and 95th percentiles of the distribution of 20-year mean changes are given for 2081–2100 in the four RCP scenarios. (Bottom) Maps of precipitation changes in 2016–2035, 2046–2065 and 2081–2100 with respect to 1986–2005 in the RCP4.5 scenario. For each point, the 25th, 50th and 75th percentiles of the distribution of the CMIP5 ensemble are shown; this includes both natural variability and inter-model spread. Hatching denotes areas where the 20-year mean differences of the percentiles are less than the standard deviation of model-estimated present day natural variability of 20-year mean differences. Figure from IPCC 2013.

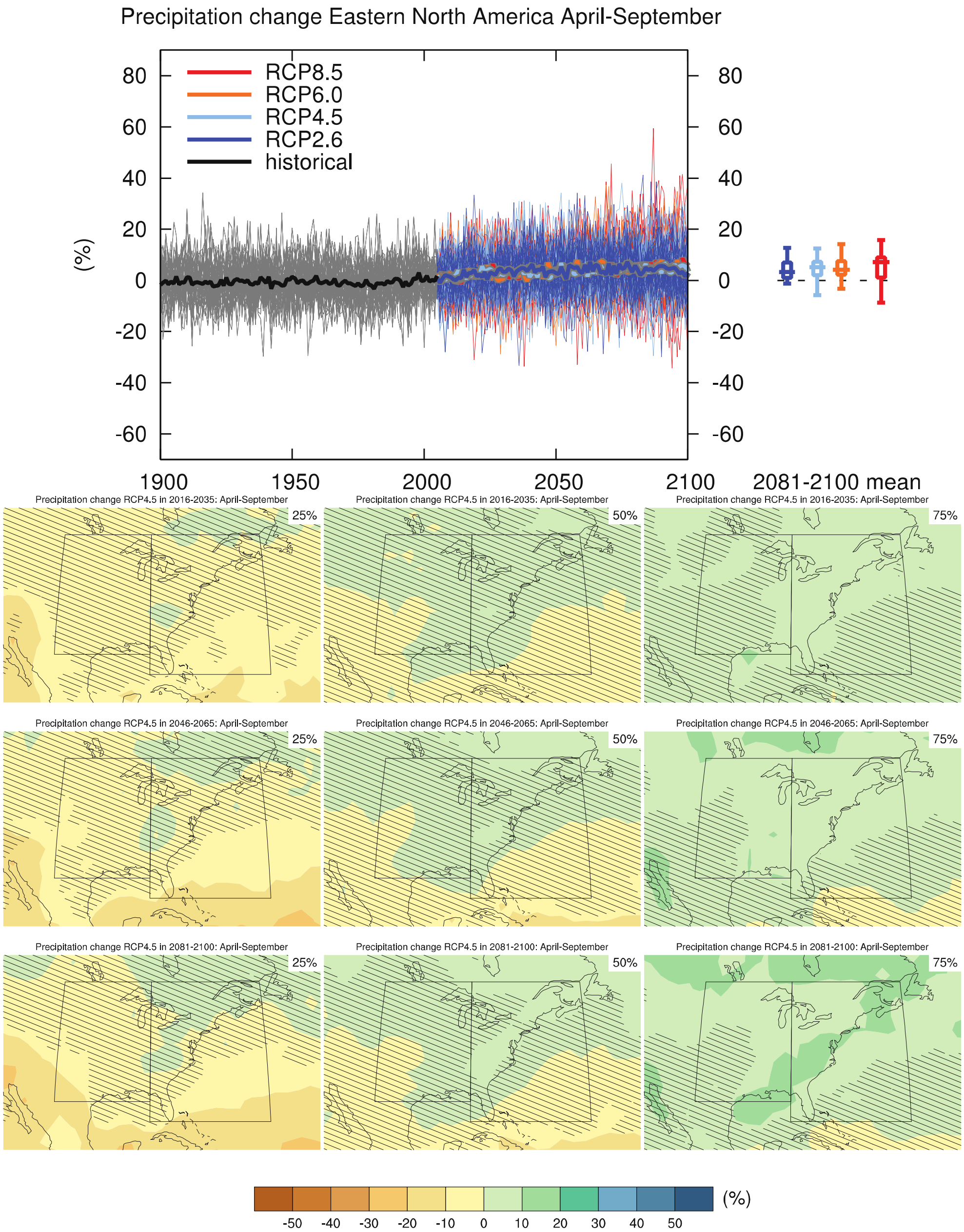

Figure 18.6. (Top) Time series of relative change relative to 1986–2005 in precipitation averaged over land grid points in Eastern North America (25°N to 50°N, 85°W to 60°W) in April to September. Thin lines denote one ensemble member per model, thick lines the CMIP5 multi-model mean. On the right-hand side the 5th, 25th, 50th (median), 75th and 95th percentiles of the distribution of 20-year mean changes are given for 2081–2100 in the four RCP scenarios. (Bottom) Maps of precipitation changes in 2016–2035, 2046–2065 and 2081–2100 with respect to 1986–2005 in the RCP4.5 scenario. For each point, the 25th, 50th and 75th percentiles of the distribution of the CMIP5 ensemble are shown; this includes both natural variability and inter-model spread. Hatching denotes areas where the 20-year mean differences of the percentiles are less than the standard deviation of model-estimated present-day natural variability of 20-year mean differences. Figure from IPCC 2013.

Regional Climate Projections

The global model results discussed above clearly show relatively little regional spatial resolution. This is particularly troublesome for decision makers at the regional level, as many users are unable to utilize GCM data that are on a coarse spatial grid (e.g. Obeysekera et al. 2011). There are a number of different statistical and dynamical techniques for downscaling the global scale models to the regional level (see also Chapter 17, which discusses downscaling of climate predictions for regional studies). In brief, dynamical downscaling translates large-scale GCM data to a finer grid using a regional climate model (Giorgi et al. 2001, 2009; Bastola and Misra 2014; among many others), and statistical downscaling uses assumptions of the relationships between large-scale fields and local climate (Wood et al. 2004; Maurer et al. 2007; among many others). Two popular datasets currently in use are the archive of statistically downscaled CMIP3 and CMIP5 Climate and Hydrology Projections (DHCP, Brekke et al. 2013) and the World Climate Research Programme (WCRP) Coordinated Regional climate Downscaling Experiment (CORDEX) (Giorgi et al. 2009), both of which are publically available. For CMIP3, the North American regional Climate Change Assessment Program (NARCCAP; Mearns et al. 2012) provides dynamically downscaled results. The interested reader is encouraged to visit the NARCCAP project (http://www.narccap.ucar.edu).

Statistical and dynamical downscaling of climate projections has often been used over the southeast and Florida. In studying the hydrological system of the Tampa Bay region, Hwang and Graham (2014) emphasized the importance of choosing the correct statistical downscaling that preserves the precipitation characteristics of the region in order to simulate the streamflow variations. Hwang et al. (2011) evaluated the fifth-generation Pennsylvania State University-National Center for Atmospheric Research Mesoscale Model (MM5) to dynamically downscale precipitation over the Tampa Bay region, and found the spatial patterns of precipitation to be realistic on daily, seasonal, and inter-annual timescales; they consider the data useful for multidecadal water resource planning in Tampa Bay. In another dynamical downscaling effort, Stefanova et al. (2012) studied seasonal, sub-seasonal, and diurnal variability of rainfall from the Center for Ocean-Atmospheric Prediction Studies (COAPS) Land-Atmosphere Regional Reanalysis for the Southeast at 10km resolution (CLARReS10), and found that that the downscaled reanalyses agreed with station and gridded observations for seasonal distribution and diurnal structure, but total precipitation was overestimated. CMIP3 climate projections were downscaled using this methodology, titled the COAPS Land-Atmosphere Regional Ensemble Climate Change Experiment for the Southeast United States at 10-km resolution (CLARREnCE10). Ning et al. (2011, 2012) use a Self-Organizing Map (SOM) strategy to statistically downscale CMIP5 precipitation over the mid-Atlantic region, determining that downscaling reduced the inter-GCM uncertainties for this region; the SOM strategy has been expanded to include Florida. For temperature, Keellings (2016) assessed the DHCP historical simulations and found that the mean and distribution of temperature matched well with observations, while extreme maximum daily temperatures were not well simulated.

Specific to Florida and based on CMIP3, Obeysekera et al. (2015) determined that for 2060, reasonable estimates for projected precipitation and temperature changes are +/- 10% and 1.5 degrees C, respectively. For CMIP5 (using DHCP), Dessalegne et al. (2016) found a wet bias in future precipitation, and percent changes in precipitation that range from -2.6 to 20.2% and changes in temperature ranging from 0.4 to 3.7 degrees C, depending on the RCP and time-period considered. However, Obeysekera et al. (2015) also pointed out the need for more information on seasonality of projected changes and extremes.

Fig. 18.7 shows the mid-century (2041 –2070) summer season (June to August) rainfall response to a relatively strong emission scenario from one global model (top) and three different regional NARCCAP models (remaining panels). All three of these regional models are forced by the particular global model at the regional boundaries of the North American sector. Focusing on Florida, it is clear that the projections from the regional models have considerably more spatial heterogeneity than the corresponding global model projections. Unfortunately, the regional models give remarkably different results on even relatively large scales. These differences are easily seen over the state of Florida, where one of the regional models has a reduction in rainfall, one is neutral, and one has a sizable increase in rainfall. This is precisely why regional climate projection remains a scientific challenge, and projections need to be presented in robust probabilistic format; however, we also note that these results are based on climate models included in CMIP3.

A more regional view of the precipitation change, though still on a coarse grid scale, is shown in Fig. 18.8 for the southern tier of the US and Caribbean in 2080–2099, with respect to 1986 – 2005 in June to September (left) and December to March (right) for the RCP4.5 scenario with 39 CMIP5 models. Because Florida's climate is modulated by many modes of natural variability (see Chapter 17), inter-decadal trends can be difficult to interpret, and there can be prolonged dry and wet periods related to decadal variability (Christensen et al. 2013; and references therein). CMIP5 models project an ensemble mean decrease in precipitation in precipitation over southern Florida and an increase in northern Florida in JJAS. In DJFM, there is an increase in precipitation. These results are robust over northern Florida (light hatching).

Though these results are more regionally focused, DHCP data has a spatial resolution more relevant to Florida, provided on a 0.125 degree x 0.125 degree grid as opposed to a 1.0 degree grid. Fig. 18.9 shows maps of the projected changed change in precipitation for 71 CMIP5 models and ensemble members. This Figure is intended to be analogous to Fig. 18.8, though it is shown as the percent change in precipitation and has not been normalized by the global mean surface temperature change as in Fig. 18.8. The downscaled results largely agree with the coarse-scale CMIP5 results, with decreasing precipitation in southern Florida and increasing precipitation in northern Florida in JJAS, and increasing precipitation overall in DJFM. We also note that results are robust across peninsular Florida in DJFM, whereas we only see robustness in the northern and extreme southernmost part of the domain in JJAS (stippling).

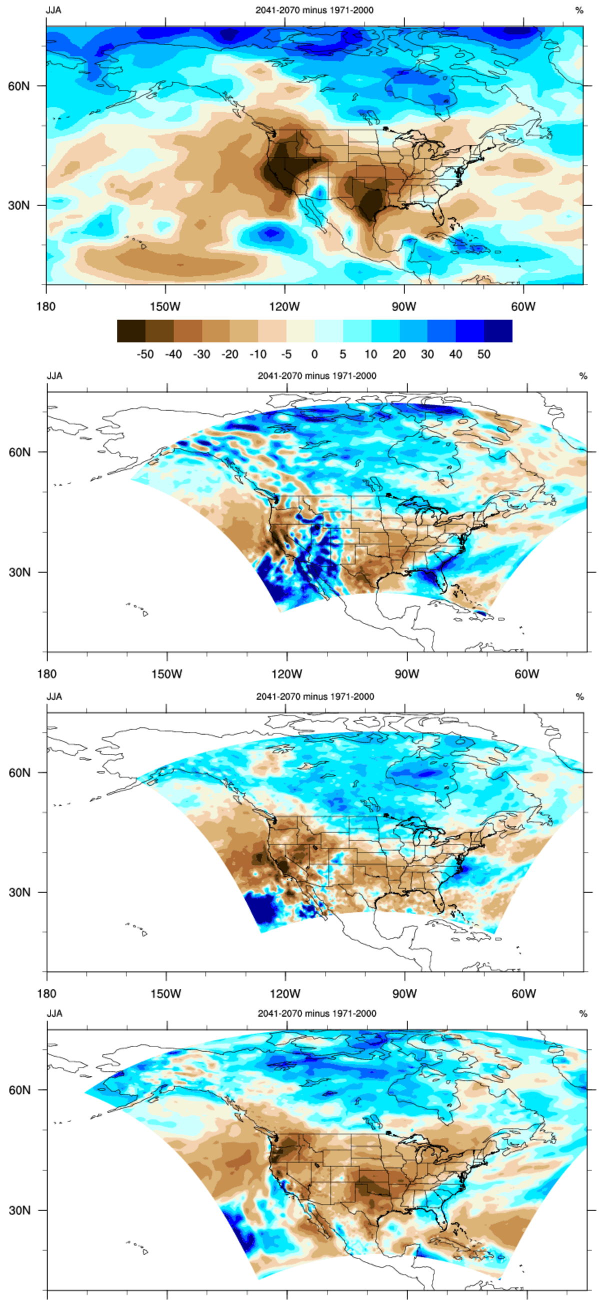

Figure 18.7. Panels show projections for North American June –August rainfall percent change during the mid-century (2041 –2070) based on a relatively high emission scenario for (top) a global model and for (remaining) three different regional models that are driving by the global model. Results are from the NARCCAP project.

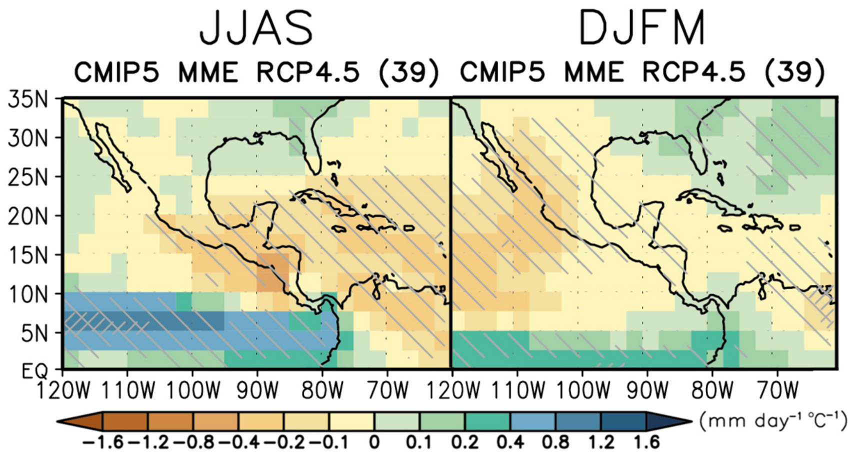

Figure 18.8. Maps of precipitation changes for southern North America and the Caribbean in 2080 –2099 with respect to 1986 –2005 in June through September (JJAS, left) and December through March (DJFM, right) in the RCP4.5 scenario with 39 CMIP5 models. Precipitation changes are normalized by the global annual mean surface air temperature changes in RCP4.5. Light hatching denotes where more than 66% of models have the same sign with the ensemble mean changes, while dense hatching denotes where more than 90% of models have the same sign with the ensemble mean change. Figure adapted from IPCC 2013 (Chapter 14).

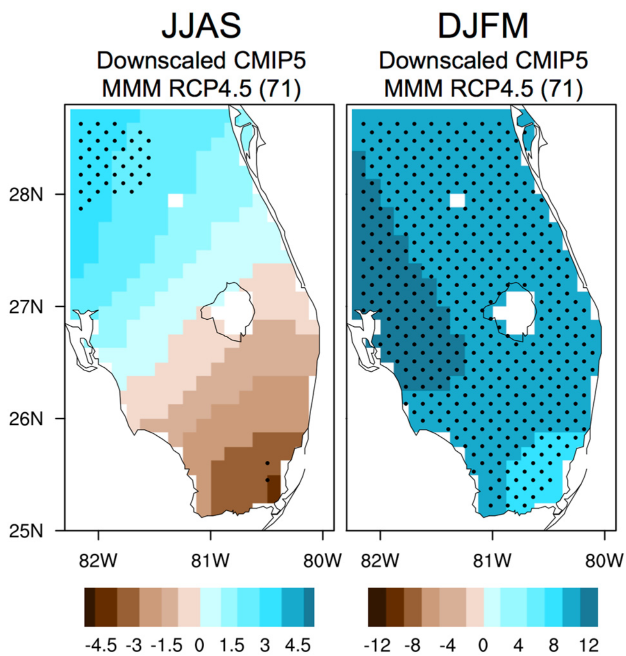

Figure 18.9. Maps of downscaled precipitation changes for peninsular Florida in 2080–2099 with respect to 1986–2005 in June through September (JJAS, left) and December through March (DJFM, right) in the RCP4.5 scenario with 71 CMIP5 models and ensemble members, from DHCP data. Precipitation changes are given as percent change in JJAS or DJFM from 1986–2005. Stippling denotes where more than 66% of models have the same sign with the ensemble mean changes.

For regions like Florida, whose terrestrial climate is dependent on the strong but mesoscale (of the order of ~10s of km) ocean currents (e.g. the Loop Current system), which transport warm waters from the tropics to the subtropical and higher latitude region, it becomes even more challenging to simulate or project the regional climate. For example, Misra et al. (2016) showed that the global models have significant errors in simulating the Loop Current. More recent publications point to conflicting estimates on the observed trends of the strength of the western boundary currents (Miller 2017). The readers are referred to Chapter 13 of this book for further discussion of the projected climate of the oceans around Florida.

Indicators as Tools for Developing Scenarios

Indicators estimated from simulations of global models, downscaled models, or observed climate variables can be used to develop scenarios at a local scale (e.g. a farm). Fig. 18.9 shows a decrease in precipitation during summer and an increase in precipitation during winter in South Florida. These changes can be translated using indicators to communicate technical data in relatively simple terms that portray the interrelationships among climate and other physical and biological elements of the ecosystem to help reveal evidence of the discernible impacts of climate change. For example, decreases in summer precipitation in South Florida is translated to trends (e.g. increases in drought, dry spells). Incremental scenarios that can be estimated from these indicator trends are +5%, +10%, +15%. These scenarios provide useful information for sustainable water resource planning and management in crop production and urban water supply. Similarly, increases in winter precipitation values in South Florida can be translated to trends (e.g. increases in flooding, wet spells indicators) etc. Incremental scenarios can be estimated from these indicator trends (e.g. +5%, +10%, 15%). These scenarios provide useful information for stormwater management and wetland management.

For example, a change in temperature (e.g. 0.5 °C) can translate to change in frost that translates to earlier spring and/or later fall seasons. Minimum temperature is the climate variable. Examples of indicators estimated from minimum temperature that portray the interrelationships among climate and the ecosystem can be frost day, last spring freeze, first fall freeze, and length of growing season. A frost day in this case is defined as a day with minimum temperature < 0 °C. Changes in the indicators are observed in Floridaand can provide important insights on the factors, processes, and structures in the ecosystem (e.g. deciding the planting day or variety of agricultural crops, the flowering of flora, the changes in the fauna life cycle, water requirement of flora and fauna). Changes in the near-term and long-term climate projections and decadal climate predictions, when translated to changes in indicators, promote developing adaptation and mitigation strategies that can protect and conserve Florida's unique ecosystems and natural resources.

Decadal Climate Prediction

Up to this point, we have only discussed results from projections. Typically, these results are shown in such a way as to minimize the internally generated climate variability. This minimization is often done by taking multi-year time averages. However, when examining the near-term there is a possibility that the internally generated near-term climate could be important and perhaps even predictable. Fig. 18.1 is suggestive in this regard. For instance, during the period 2005–2012, the projections are largely warmer than the observational estimates. The trace from the observational estimates lies in the lower tail of the climate projections. Is this because the models produce too much warming for a given level of external forcing (i.e., their so-called climate sensitivity is too large)? Alternatively, this could be because the projections make no attempt to capture the phasing of the internally generated climate variability. This is where the new science of decadal prediction comes in. As noted earlier, decadal predictions are dependent on both the initial state and the external forcing, and as such have the potential to predict the internally generated climate variability and capture the externally forced response (see Box 11.1 in Kirtman et al. 2013). Fig. 18.8 which follows a similar format as Fig. 18.1, shows the near-term projections and some early attempts at decadal predictions (black and red hatched regions). The decadal predictions suggest less warming than the projections in better agreement with the observational estimates (see Meehl and Tang 2012 and Smith et al. 2012 for details).

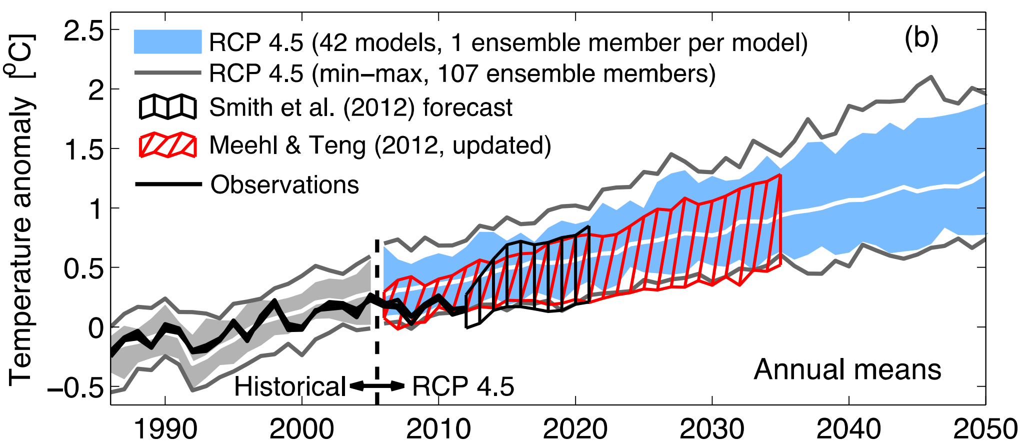

Figure 18.8. Projections of global mean, annual mean surface air temperature 1986–2050 (anomalies relative to 1986–2005), with four observational estimates as shown in Fig. 18.1. The shading illustrates the 5 to 95% range (grey and blue shades, with the multi-model median in white) of annual mean CMIP5 projections using one ensemble member per model from RCP4.5 scenario, and annual mean observational estimates (solid black line). The maximum and minimum values from CMIP5 are shown by the grey lines. Red hatching shows 5 to 95% range for predictions initialized in 2006 for 14 CMIP5 models applying the Meehl and Teng (2012) methodology. Black hatching shows the 5 to 95% range for predictions initialized in 2011 for eight models from Smith et al. (2013). Figure taken from Kirtman et al. (2013).

Since the science of decadal prediction is still relatively immature, it is not ready for regional decision support. However, there it holds considerable potential for providing near-term probabilistic information that takes both the external forcing and the internally generated variability into account (Meehl et al. 2009, 2013). As an example, we show (Fig. 18.9) the five-year forecast (2016-2020) for surface air temperature from a number of dynamic and statistical prediction systems (details in Smith et al. 2013).

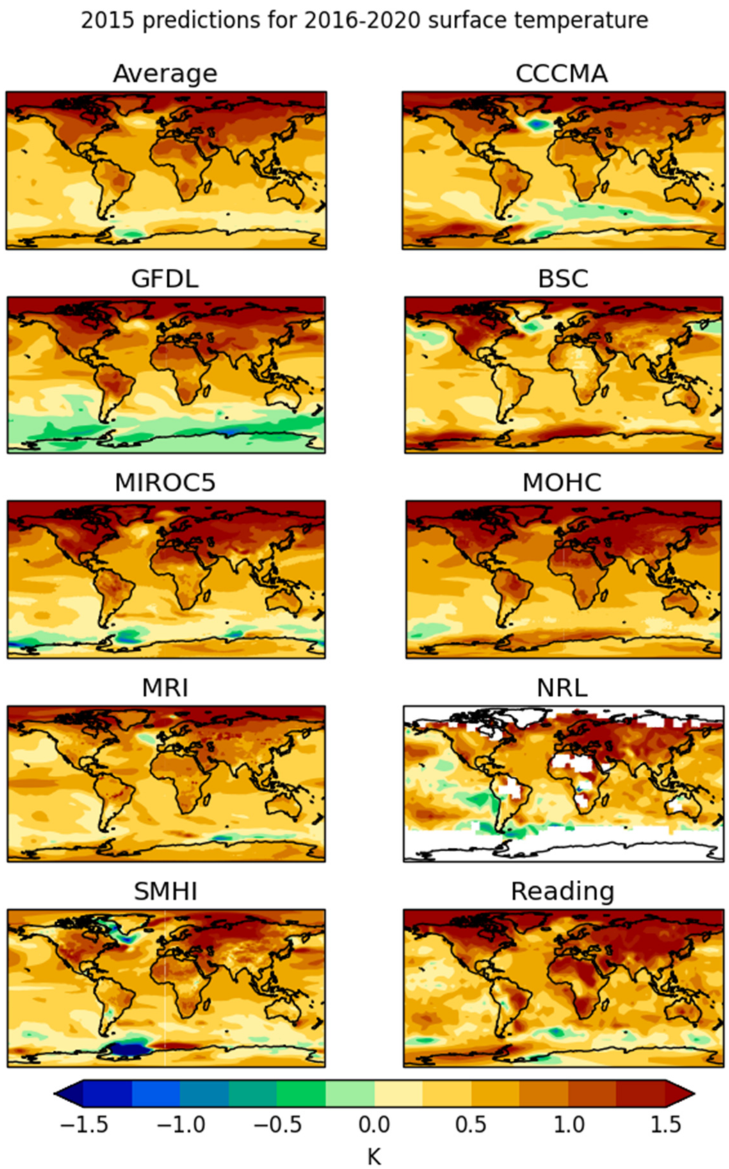

Figure 18.9. Decadal predictions for 2016 – 2020 from a number of different dynamic and statistical prediction systems (see Smith et al. 2013).

Final Remarks

The results described above (and in Chapter 17) clearly demonstrate that the science of regional externally forced and internally generated climate variability remains unresolved. Florida's climate, in particular, is especially difficult to project because of its narrow peninsula and the complex air – sea interactions associated with the surrounding oceans. Florida also sits at the boundaries between the tropics and the extra-tropics, and small shifts in how the global models represent the tropics and subtropics have profound impacts over Florida. Indeed, the global models have large uncertainties in the boundary between the tropics and extra-tropics, leading to large uncertainties in Florida projections from global models. The Fifth Assessment Report of the IPCC notes the need for extreme caution when using the global models for regional projections (see box 11.2 in Kirtman et al. 2013).

The climate science community clearly understands that adaption decisions need robust regional information, and that the current generation of global models are not sufficient in this regard. As such, there are a number of efforts to produce regional climate information using a variety of dynamical and statistical methodologies. All of these approaches show promise, but the science is relatively immature and robust projections and predictions will ultimately need to be tailored to the specific decision support requirements.

In terms of near-term climate, decadal prediction seems to also hold some promise. Part of the reason for this is that decadal predictions can be rigorously verified in terms of both the internally generated and externally forced variability, and they can be calibrated for robust probabilistic information. Moreover, decadal prediction can be performed at considerably higher spatial resolution than is possible with global projections; and there is compelling results indicating that this increased resolution will improve the fidelity of the predictions (see Siqueira and Kirtman 2016).

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