

Impacts of Climate Change and Variability on
Transportation Systems and Infrastructure

The Gulf Coast Study, Phase 2

Temperature and Precipitation Projections for the Mobile Bay Region

Final Report

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SUMMARY

Global climate change is already affecting average conditions in many locations around the world. Over the coming century, climate is expected to continue to change as the result of both past and future emissions of heat-trapping gases from human activities. Impacts include increasing temperatures, shifting precipitation patterns, and changes in the risk of some extreme events.

The purpose of this report is to document observed trends and projected future changes in temperature and precipitation-related climate indicators for the greater Mobile Bay area. These indicators were selected by the Gulf Coast 2 project team as being particularly relevant to analyzing the potential for climate change to have a negative impact on transportation infrastructure and operations in the Gulf Coast region. The indicators reflect thresholds relevant to infrastructure design that can be projected using climate modeling tools and techniques. Data from five long-term weather stations in the region, Bay-Minette, Coden, Fairhope, Mobile Airport, and Robertsdale, are used in this analysis. Results from this report inform the temperature and precipitation-related analyses of the companion document, *Gulf Coast Study, Phase 2: Task 2, Climate Variability and Change in Mobile, Alabama*.¹

Future projections are based on simulations from 10 global climate models, corresponding to three different futures: the IPCC SRES higher (A1fi), mid-high (A2), and lower (B1) emission scenarios. Statistical downscaling was performed using the Asynchronous Regional Regression Model (ARRM). Biases in simulated historical temperature and precipitation were evaluated by comparing simulated values with observations. In general, biases were larger for precipitation than for temperature, and for quantiles near the tails of the distribution as compared to the mean.

Over the past 50 years, the Mobile Bay region has experienced significant and consistent trends in fall temperatures (cooling), consecutive days per year over 95 and 100°F (increasing), summer and fall precipitation (increasing), and most quantiles of 24h, 48h, and 96h cumulative precipitation (increasing).

In the future, temperatures are projected to warm by an average of 1.5°F over the near term, 2.4-4.6°F by mid-century, and 3.2-7.7°F by end-of-century. Greater warming is projected for later summer and fall as compared to other months. Hot temperature extremes are projected to increase while cold temperature extremes are projected to decrease, with greater differences between higher vs. lower emissions scenarios for warm temperature extremes (e.g. 7-day hottest temperature) as compared to cold temperature extremes (e.g. coldest day of the year). Before the end of the century, the number of days with maximum temperature exceeding 95°F could increase by a factor of 3 under lower emissions and 10 under higher.

Little change is expected in annual average precipitation, although fall precipitation is projected to continue to increase. Nearly all precipitation extremes are projected to

¹ Available at: http://www.fhwa.dot.gov/hep/climate/gulf_coast_study/index.htm

increase in the future, although with little difference between the values for various time periods or for higher as compared to lower emissions.

In addition to summarizing potential climate changes in the greater Mobile Bay region, this report also lays out a methodology that can be used to replicate a regional climate assessment such as this in other regions and for other climate indicators.

SECTION 1: BACKGROUND

In the past, climate variations were caused by natural forces. These include external changes in amount of energy the Earth receives from the Sun, or the cooling effects of dust clouds from powerful volcanic eruptions, amplified by natural feedbacks within the earth-ocean-atmosphere system. Today, however, the climate is being altered by both natural and human causes (Hegerl et al., 2007). Since the Industrial Revolution, atmospheric levels of heat-trapping gases such as carbon dioxide and methane have been rising, primarily due to increased consumption of fossil fuels such as coal, oil, and natural gas (Andres et al., 1999; Stern & Kaufmann, 1998).

Atmospheric levels of carbon dioxide are now higher than they have been at any time in at least the last 800,000 years (Lüthi et al., 2008). Average surface temperatures in the Northern Hemisphere have risen by 1.3°F (0.75°C) over the past 150 years (Trenberth et al., 2007). Based on these and many other lines of evidence, the Intergovernmental Panel on Climate Change (IPCC), which represents the work of thousands of climate scientists around the world, has concluded that it is very likely that most of the climate changes observed over the last fifty years have been caused by emissions of heat-trapping gases from human activities (IPCC, 2007). Subsequent analyses have strengthened this conclusion, with more recent studies suggesting that human influence is responsible for most of the warming over the last one hundred and fifty years, and as much as all of the warming over the last sixty years (Huber & Knutti, 2011; Foster & Rahmstorf, 2011; Gillett et al., 2012).

Over the coming century, climate will likely continue to change in response to both past and future emissions of heat-trapping gases from human activities (IPCC, 2007). At the global scale, temperature increases between 4°F up to 13°F are expected by end of century, accompanied in many regions of the United States by increases in extreme heat and heavy precipitation events (USGCRP, 2009).

Alabama's climate – together with that of the rest of the United States - is expected to reflect changes occurring at the global scale (USGCRP, 2009). This report describes the changes in long-term climate and climate variability that might be expected over the coming century for five long-term Global Historical Climatology Network (GHCN) weather stations in the Mobile Bay region of Alabama, located in Bay-Minette, Coden, Fairhope, Mobile (airport), and Robertsedale. Future projections are based on three future emissions scenarios (higher, mid-high, and lower), and simulations from ten different global climate models.

Section 2 lays out a general framework for conducting regional climate impact analyses, describes the scenarios and models, and explains the statistical downscaling model used to generate high-resolution projections for the individual weather stations.

Section 3 discusses how infrastructure-relevant temperature metrics are likely to be affected by climate change in the near future (2010-2039), by mid-century (2040-2069) and towards the end of the century (2070-2099) relative to a historical baseline of 1980-2009.

Section 4 describes projected changes in precipitation indices for those same future time periods.

Section 5 provides guidance on understanding and interpreting the range of uncertainty in future projections, and evaluates the ability of downscaled climate projections to reproduce observed historical variability for the Mobile stations.

Finally, Section 6 concludes with a discussion of the implications of climate change for the Mobile Bay region, including the potential for climate projections to inform adaptation planning.

SECTION 2: DATA AND METHODS

Assessing the potential impacts of climate change on a given location and sector is a challenging task. It begins with integrating multiple datasets and model outputs that cover a range of spatial and temporal scales. Inputs and methods must be translated across disciplinary boundaries. Reasonable ways must be found to quantify the uncertainty inherent to future projections before synthesizing the results into a coherent picture of potential impacts.

Although challenging, it is important to assess climate impacts because the information generated can be valuable to long-term planning or policies. For example, projected changes in heating or cooling degree-days can be incorporated into new building codes or energy policy. Shifts in the timing and availability of streamflow can be used to redistribute water allocations or as incentive for conservation programs. Projected changes in growing season and pest ranges can inform crop genetics research and agricultural practices.

The primary challenge in climate impact analyses is the reliability of future information. A common axiom warns that the only aspect of the future that can be predicted with any certainty is the fact that it is impossible to do so. However, although it is not possible to *predict* the future, it is possible to *project* it. Projections can describe what would be likely to occur under a set of consistent and clearly articulated assumptions. For climate change impacts, these assumptions should encompass a broad variety of the ways in which energy, population, development and technology might change in the future.

By quantifying a range, future projections can be expressed in terms of *risk*. Risk is a concept that is already incorporated into decision-making at all levels: by individuals who routinely rely on a sense of risk to guide their purchases, from vitamins to motor vehicles; by businesses that use risk analyses as input to strategic planning; and by governments for whom risk assessment is an integral part of both domestic and foreign policy.

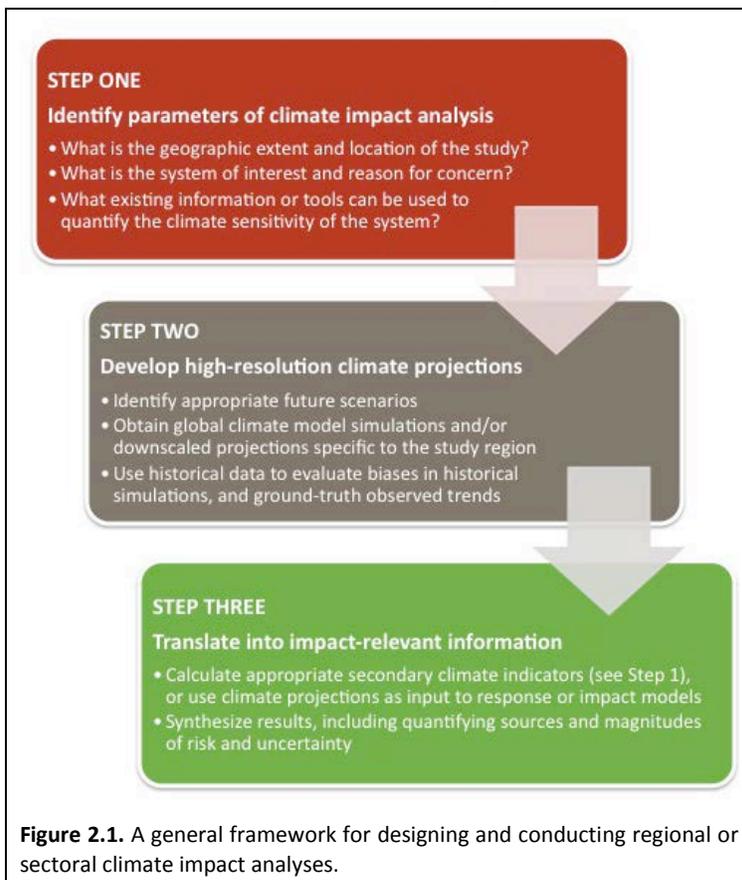
This section first describes a general approach to developing the projections needed to quantify the risks of climate impacts for any regional or sectoral analysis. This general framework is then applied to quantify potential effects on transportation infrastructure in the greater Mobile Bay region. The remainder of this section describes the specific datasets and methods selected for, and used in, this analysis. These include observational data, global climate models, future scenarios, and downscaling methods. Where appropriate, the extent to which these datasets and tools can be applied to other regions or sectors is also discussed.

[A General Framework for Developing and Applying Climate Projections to Regional Impact Analyses](#)

Each regional impact analysis has its own unique requirements. However, there are some common datasets, tools, and methods that can be combined in ways that are relevant across a broad range of applications (Figure 2.1).

Most analyses begin by identifying the parameters of the study. In this **first step** there are at least three key questions to consider that will determine the type of data, tools, and methods used in the analysis:

1. *What is the geographic extent and region of interest?* For example: a watershed, a city, a state, or an eco-region.
2. *What is the system and the concern associated with it?* For example: the long-term prospects for water supply from a certain reservoir; the cost of operating or maintaining city buildings; the public health response to deteriorating air quality; or the ecological impacts of an invasive species moving into the region.
3. *What existing information or tools can be used to quantify the potential impacts of climate change on this system?* For example: a model already used for water management planning by the district; historical data that can be used to correlate building maintenance costs with temperature variability; a dynamical air quality model coupled with epidemiological response functions to certain pollutant levels; or a statistical climate envelope modeling package that, when combined with historical climate data, can calculate the implied limits on invasive species' ranges.



The **second step** is to assemble the scientific data and models needed to develop future projections. There are several different approaches to doing so, depending on the answer to question 3 above (what information can be used to quantify the sensitivity of the system to climate?).

When the answer to question 3 is “not much,” a study might need to begin by quantifying the response of a system to a fixed perturbation in temperature or other climate conditions that is simply added to observed conditions—for example, the impact of a steady-state 2 and 4°C warming, or a sustained precipitation decrease of 25% and 50%). This type of approach has been used for

many early-stage climate impact analyses to determine the sensitivity of the system to plausible levels of change. The magnitude of the perturbation need only lie within the

reasonable range of expected changes, and can be simply read from existing plots such as those available in USGCRP (2009) or generated using the Climate Wizard tool (<http://www.climatewizard.org>).

When the answer to question 3 includes long-term data and/or modeling tools that capture the effect of climate variability and/or change on the system of interest, however, then a different approach is possible. If the sensitivity of the system can already be determined, then it is possible to use time-dependent simulations that track the simultaneous evolution of changes in multiple aspects of climate.

In contrast to perturbation analyses, assessing the actual likelihood or risk of climate impacts requires global climate model simulations driven by future scenarios of human emissions. The spatial accuracy of global climate models is limited to the regional scale, so downscaling is commonly used to transform large-scale changes in climate into more localized conditions similar to those measured at long-term weather stations. The ability of the climate and downscaling models to simulate local conditions can be evaluated by validating historical simulations on a set of independent observed data.

Climate science can generate projections of basic climate variables, such as daily maximum temperature or 24h cumulative precipitation. For climate impact analyses, however, these projections must be translated into impact-relevant information. In some cases, the translation step consists of calculating projected changes in secondary climate indicators already used in planning or known to be relevant. Indicators are generally specific to each study, consisting of the weeks per year exceeding a given amount of rain, for example, corresponding to a local sewer overflow threshold; the average number of days per year with sufficient snow to require plowing and salting the roads; or the risk of temperature in summer exceeding a level that would affect crop yields.

In other cases, climate projections are used as input to an additional set of climate response, or impact, models. For example, daily temperature, humidity, rainfall and solar radiation can replace meteorological observations in ecological models to simulate the effects of climate change on a range of systems, from forest nutrient cycles to crop yields. Dynamic vegetation models driven by climate projections can simulate changes in wildfire frequency and area burned. Three-dimensional output fields from climate models can be used to drive air quality models, estimating the impact of warmer temperatures and changes in atmospheric circulation patterns on air quality and pollution. Empirical epidemiological models can combine climate projections with observed response functions to quantify the potential impacts of extreme heat on respiratory disease and even mortality.

The **third step** in Figure 2.1 is to synthesize the results of the analysis and quantify the uncertainty to assess future risk. As discussed in more detail in Section 5, near term uncertainty is dominated by natural variability (Hawkins & Sutton, 2009; 2011). Natural variability is largely chaotic, a function of heat exchanges between the ocean and the atmosphere, volcanic eruptions, variations in solar energy, and other processes unrelated to human activities. Natural uncertainty can be addressed by using input from multiple climate model simulations, each with slightly different initial conditions. Future projections of climate should always be summarized over climatological time scales—typically, 20 to 30 years--to determine the risk of a given event or magnitude of change over that period as a whole.

Towards mid-21st century, scientific understanding of the climate system becomes the largest contributor to the range in projections. Model uncertainty can be addressed by using the projections from multiple climate models. Each climate model represents the various components and processes that make up the Earth's climate system in slightly different ways. These differences affect how sensitive the simulated Earth's climate is to human emissions, as well as the regional distribution of climate change.

By the end of the century, the contribution of human emissions increases in importance. For temperature, the future scenario becomes the dominant factor determining the magnitude of future change (Hawkins & Sutton, 2009, 2011). Scenario uncertainty can be addressed by using a broad range of future scenarios, including both increases and decreases in future emissions of heat-trapping gases from human activities. For analyses after mid-century, projections should not be averaged across scenarios; rather, each scenario should be compared to quantify the role of human choices in determining the magnitude of future impacts.

Two Examples: Assessing Climate Impacts for Chicago and the U.S.

The general framework described above is similar to that used in previous assessments. Two examples illustrate how this process can be used to frame analyses with very different spatial scales, motivations, and purposes. The first example is a local study of climate impacts on the city of Chicago (Wuebbles et al., 2010; Hayhoe et al., 2010a,b,c). The second is a national study of the impacts of climate change on multiple U.S. regions and sectors (USGCRP, 2009).

CHICAGO

Step One. This analysis was initiated by the city of Chicago's Department of Environment and the Chicago Climate Action Plan advisory committee. They decided that the Action Plan should be based on scientific projections of how climate change would affect local conditions in Chicago, projections which would in turn inform a risk analysis of climate impacts on city operations under a higher and lower emissions future. As the Action Plan was specific to Chicago, the geographic extent of the analysis was limited to the area under the jurisdiction of the city itself.

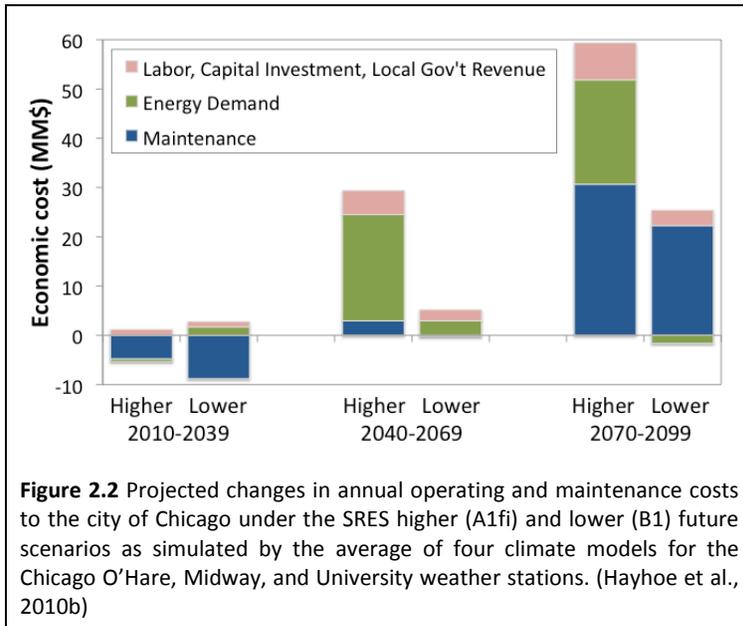
The specific concern was how climate change would affect city operations, as represented by city departments and other organizations such as the Chicago Transit Authority and the Chicago School Board. No models or planning tools were being used to incorporate climate or weather-related variables into city planning, but the climate impacts team (consisting of scientists and risk management experts from the international management consulting firm Oliver Wyman) were given full access to city departments to collect information on how each department might be impacted by climate change.

Step Two. In order to capture the full range of projected future change, the SRES A1fi (higher) and B1 (lower) emission scenarios were used as the basis for future projections. Four global climate models had daily simulations available for these scenarios (CCSM3, GFDL CM2.1, HadCM3 and PCM). Long-term station data was obtained for the three stations within the city of Chicago (O'Hare, University, and Midway) as well as for additional suburban stations in order to generate a broader base of future projections. Global model simulations were downscaled using a statistical quantile regression

approach to provide daily projections of maximum and minimum temperature and precipitation.

Step Three. To quantify the impact of climate change on city departments, the city invited representatives from each department to a meeting where climate scientists presented sample indicators, including projected changes in the number of days per year over a given temperature threshold, the frequency of heavy rainfall events, and projected changes in winter snowfall. These examples were used to demonstrate the type of information that could potentially be provided to the city.

The risk assessment team then followed up on this initial step with individual meetings with each city department to identify actual indicators relevant to that department. These meetings resulted in a list of over 100 secondary indicators that affected operations costs in 14 departments. These included the frequency of freeze/thaw events affecting road conditions and pothole formation; number of days per year over a specific temperature threshold at which rapid transit rails warped; accumulated heating and cooling degree-days that are proportional to energy use; and precipitation exceedences that could lead to storm sewer overflow.



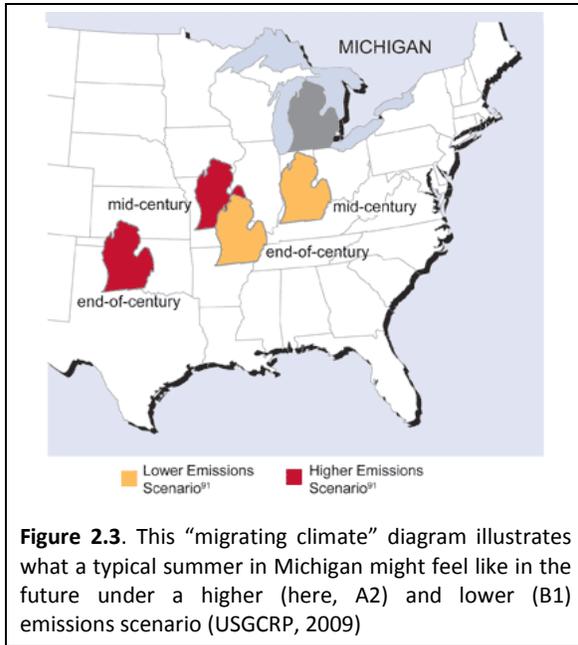
This list of indicators was then provided to the scientific team, which calculated projected changes in these indicators as simulated by each global model, corresponding to each future scenario, and handed these back to the risk assessment team. The team then calculated the costs to each city department for three future time periods (2010-2039, 2040-2069, 2070-2099) under higher and lower emissions based on the risk assessment model they had

built using the data collected from each department. The resulting costs (shown in Fig. 2.2) were then provided to the city to use as input to decisions on adaptation and mitigation.

UNITED STATES

Step One. This analysis was initiated by the U.S. Global Change Research Program’s mandate to provide a national assessment of climate change impacts for the United States. Previous assessments had divided the U.S. into 8 regions: Northwest, Southwest, Great Plains, Midwest, Northeast, Southeast, Islands, and Alaska. Each of these regions formed the basis for a chapter in the assessment.

The purpose of the assessment was to provide consistent analysis of historical trends, to generate projections of future changes in average and extreme temperature and precipitation, and to synthesize available information on the most important aspects of climate change for each region.



Step Two. This assessment also wanted to ensure its projections captured a broad range of projected future change, from the SRES A1fi (higher) to the B1 (lower) emission scenario. However, as A1fi simulations were available from only four global climate models, simulations corresponding to the A2 (mid-high) scenario generated by 12 more global models were also used. As this was a regional assessment covering a very large geographic area, global climate model projections were downscaled to a gridded database of observed temperature and precipitation, rather than individual weather stations. Global model simulations were downscaled using a statistical quantile mapping approach that generated

monthly projections of changes in maximum and minimum temperature and precipitation, then daily values generated by sampling from the historical record.

Step Three. The purpose of the assessment was not to directly quantify climate impacts for each region, but rather to provide a consistent basis of regional climate projections within which the literature on climate impacts could be framed. For that reason, the translation process consisted of ensuring that the same type of projections was used as the basis for each regional chapter. A number of broadly-relevant secondary indicators were identified and plotted as maps, including the number of days per year over 90 and 100°F, as well as new versions of the “migrating climate” diagram shown in Fig. 2.3.

STEP ONE: Identifying the parameters of the analysis

Here, the general framework described in Figure 2.1 is applied to climate impacts on transportation infrastructure in the Mobile Bay area. This report focuses primarily on the last two steps of the general framework illustrated in Figure 2.1. Hence, only a brief overview of Step 1 is provided here.

This study focuses on the greater Mobile Bay region (see Figure 2.6 below). As this is a coastal region, the geographic extent of the study was determined by ensuring the study area included enough long-term weather stations to be sufficiently representative of the region (here, 5), but not so many weather stations as to include other more distant regions inland that could have micro-climates that differed from those of coastal Alabama.

The concern motivating this analysis of temperature and precipitation projections was the potential for changes in average and/or extreme temperature and precipitation to exceed

the engineering design thresholds of transportation infrastructure, particularly in this region. For more information on these indicators, please see *Gulf Coast Study, Phase 2: Task 2, Climate Variability and Change in Mobile, Alabama*.²

Existing temperature and precipitation metrics used in current design standards already reflected the sensitivity of these standards to climate. A list of these metrics, summarized in Table 2.1, was used to define the secondary climate indicators calculated in Step 3. The precise definition used to calculate each metric is given in the Appendix.

TEMPERATURE		PRECIPITATION	
<i>Average</i>	<i>Extreme</i>	<i>Average</i>	<i>Extreme</i>
Monthly Mean	Number of extreme heat days over 95, 100, 105, 110	Monthly Mean	24h precipitation: 0.2 nd to 50 th percentile
Seasonal Mean	Maximum number of consecutive days over 95, 100, 105, 110	Seasonal Mean	48h and 96h precipitation: mean, 0.2 nd to 50 th percentile
Annual Mean	Warmest and coldest consecutive four days: 5 th through 95 th percentile	Annual Mean	Greatest 3-day precipitation per season
Annual 50 th and 95 th percentile	Coldest historical day, probability Hottest historical 7-day period, probability		

Table 2.1. Secondary climate indicators used in this study, identified on the basis of engineering design standards.

STEP TWO: Developing and evaluating high-resolution climate projections

Scenarios: Past and Future

The Coupled Model Intercomparison Project’s “20th Century Climate in Coupled Models” (20c3m) scenario is used to drive global climate model simulations from the late 1800s through 2000 (Meehl et al., 2007). This scenario reproduces climate conditions observed over the past century as closely as possible. It includes observed changes in solar radiation, volcanic eruptions, human emissions of greenhouse gases, and emissions of other gases and particles including aerosols and air pollutants.

Future scenarios are more difficult. They depend on a myriad of factors, including how human societies and economies will develop over the coming decades; what technological advances are expected; which energy sources will be used in the future to generate electricity, power transportation, and serve industry; and how all these choices will affect future emissions from human activities.

To address these questions, in 2000 the Intergovernmental Panel on Climate Change (IPCC) developed a set of future emissions scenarios known as SRES (Special Report on Emissions Scenarios; Nakicenovic et al., 2000). These scenarios encompass a range of plausible futures by estimating the emissions resulting from a range of projections for future population, demographics, technology, and energy use (Fig. 2.4a).

In this analysis, projected climate changes under the SRES higher A1fi or fossil-intensive scenario (red line) are compared to those expected under the mid-high A2 scenario

² Available at: http://www.fhwa.dot.gov/hep/climate/gcs_overview.htm.

(orange line) and the lower B1 scenario (blue line). Typically, just two scenarios (A1fi and B1) would suffice to encompass an adequate range of future change. However, the A2 mid-high scenario was included as simulations for the A1fi higher scenario were available from only four of the ten global climate models used in this analysis.

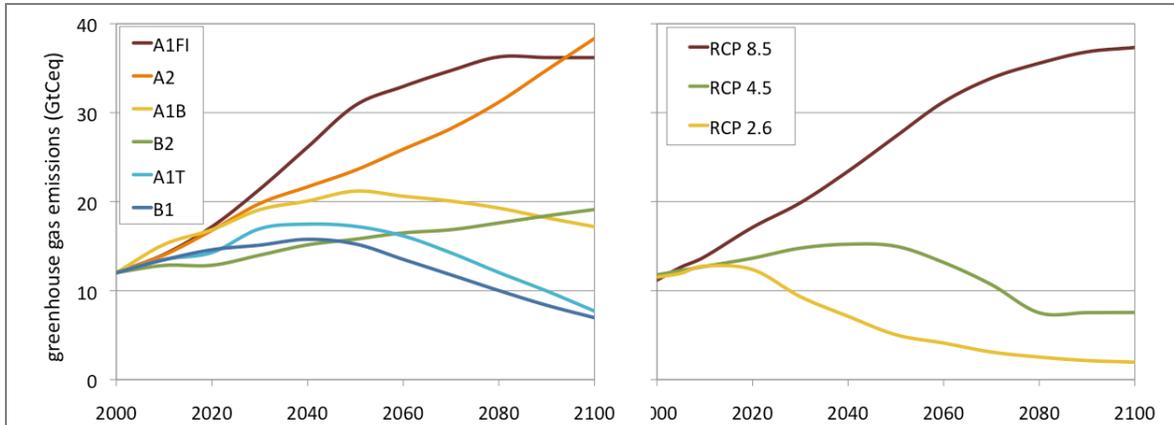


Figure 2.4 Projected future greenhouse gas emissions, in units of gigatons carbon equivalent. Non-CO₂ gases were converted to CO₂-equivalent units using a 100-year global warming potential value. Values are shown for: (a) the 2000 SRES emission scenarios, and (b) the 2010 Representative Concentration Pathways, converted from concentrations to emissions using a carbon cycle model. The SRES higher (A1fi, red), mid-high (A2, orange), and lower (B1, dark blue) scenarios are used in this analysis. SRES A1fi is similar to RCP 8.5, while SRES B1 is similar to RCP 4.5.

The A1fi higher emissions scenario represents a world with fossil fuel-intensive economic growth and a global population that peaks mid-century and then declines. New and more efficient technologies are introduced toward the end of the century. In this scenario, atmospheric carbon dioxide concentrations reach 940 parts per million (ppm) by 2100, more than triple pre-industrial levels (Nakicenovic et al., 2000).

The A2 mid-high emissions scenario imagines a more individualistic world, where each region develops relatively independently, with slow technological development. Emissions rise rapidly towards the end of the century, with carbon dioxide concentrations reaching 870 ppm by 2100 (Nakicenovic et al., 2000).

The B1 lower-emissions scenario also represents a world with high economic growth and a global population that peaks mid-century and then declines. However, this scenario includes a shift to less fossil fuel-intensive industries and the introduction of clean and resource-efficient technologies. Emissions of greenhouse gases peak around mid-century and then decline. Atmospheric carbon dioxide concentrations reach 550 ppm by 2100, approximately double pre-industrial levels (Nakicenovic et al., 2000).

As diverse as they are, the SRES scenarios still do not cover the entire range of possible futures. Since 2000, CO₂ emissions have already been increasing at an average rate of 3% per year. If they continue at this rate, emissions will eventually outpace even the highest of the SRES scenarios (Raupach et al., 2007; Myhre et al., 2009). On the other hand, significant reductions in emissions—on the order of 80% by 2050, as already mandated by the state of California—could reduce CO₂ levels below the lower B1 emission scenario within a few decades (Meinhausen et al., 2006). Nonetheless, the substantial

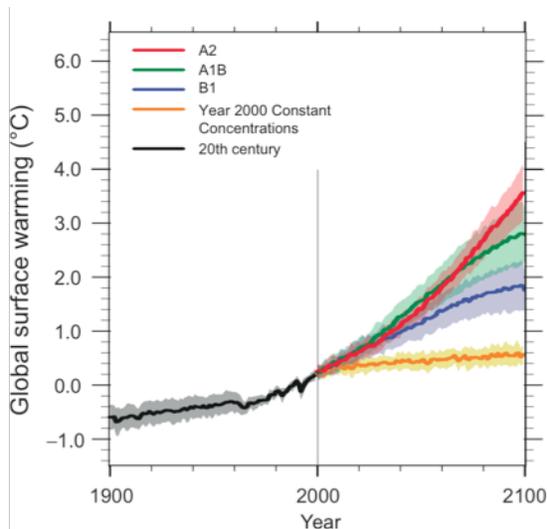


Figure 2.5 Projected future global temperature change for the SRES emission scenarios (degrees C). The range for each individual emission scenario indicates model uncertainty in simulating the response of the Earth system to human emissions of greenhouse gases. Source: IPCC, 2007

difference between the SRES higher- and lower- emissions scenarios used here provides a good illustration of the potential range of changes that could be expected, and how much these depend on future emissions and human choices. The relative importance of scenario uncertainty, as compared to uncertainty due to natural variability and the uncertainty inherent to modeling the physical climate system, is discussed in Section 5.

As of 2011, the SRES emission scenarios are in the process of being replaced by a new series of scenarios based on atmospheric carbon dioxide equivalent concentrations. These scenarios, known as Representative Concentration Pathways (RCPs), will be used as the basis for climate model simulations in support of the IPCC Fifth Assessment Report, to be published in 2012 (Moss et al., 2010).

The new RCP 8.5 scenario is very similar to the SRES A1fi higher scenario, while the new RCP 4.5 scenario is similar to the SRES B1 lower scenario (Figure 2.4b). Future climate impact assessments can therefore rely on RCP 8.5 to 4.5, or 2.6, to cover the range of plausible emission futures.

Global Climate Model Simulations

Future scenarios are used as input to global climate models (GCMs). GCMs are complex, three-dimensional coupled models that are continually evolving to incorporate the latest scientific understanding of the atmosphere, oceans, and Earth’s surface. As output, GCMs produce geographic grid-based projections of temperature, precipitation, and other climate variables and daily and monthly scales. These physical models were originally known as atmosphere-ocean general circulation models (AO-GCMs). However, many of the newest generation of models are now more accurately described as earth system models (ESMs) as they incorporate additional chemistry and biology.

Because of their complexity, GCMs are constantly being enhanced as scientific understanding of climate improves and as computational power increases. Some models are more successful than others at reproducing observed climate and trends over the past century (Randall et al., 2007; see Section 5 for more on evaluating climate simulations). However, all future simulations agree that both global and regional temperatures will increase over the coming century in response to increasing emissions of greenhouse gases from human activities (IPCC, 2007; Fig. 2.5).

Model Name	Origin	Atmospheric Resolution (horizontal, vertical)	Climate Sensitivity (°C)	Reference
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BCCR-BCM2.0	Bjerknes Centre for Climate Research, Norway	1.9° x 1.9° 31 levels	N/A	Furevik et al., 2003
CCSM3	National Center for Atmospheric Research, USA	1.4° x 1.4° 26 levels	2.7	Collins et al., 2006
CGCM3 (T47)	Canadian Centre for Climate Modelling and Analysis, Canada	2.8° x 2.8° 31 levels	3.4	Flato, 2005
CGCM3 (T63)		1.9° x 1.9° 31 levels	3.4	
CNRM-CM3	Météo-France/Centre National de Recherches Météorologiques	1.9° x 1.9° 45 levels	N/A	Salas-Mélia, 2005
ECHAM5/MPI-OM	Max Planck Institute for Meteorology, Germany	1.9° x 1.9° 31 levels	3.4	Roeckner et al., 2003
GFDL-CM2.0	National Oceanic and Atmospheric Administration (NOAA)/Geophysical Fluid Dynamics Laboratory (GFDL)	2.0° x 2.5° 24 levels	2.9	Delworth et al., 2006
GFDL-CM2.1		2.0° x 2.5° 24 levels	3.4	
PCM	National Center for Atmospheric Research, USA	2.8° x 2.8° 26 levels	2.1	Washington et al., 2000
UKMO-HadCM3	Hadley Centre/Met Office, UK	2.5° x 3.75° 19 levels	3.3	Gordon et al., 2000

Table 2.2. Description of the ten global climate models used in this analysis, including their origin and nationality, horizontal resolution, number of vertical levels, climate sensitivity defined as the equilibrium temperature change resulting from a doubling of carbon dioxide relative to pre-industrial times, and reference.

Historical GCM simulations are initialized in the late 1800's, externally "forced" by the human emissions, volcanic eruptions, and solar variations represented by the 20c3m scenario, and allowed to develop their own pattern of natural chaotic variability over time. This means that, although the climatological means of historical simulations should correspond to observations at the continental to global scale, no temporal correspondence between model simulations and observations should be expected on a day-to-day or even year-to-year basis. For example: while a strong El Niño event occurred from 1997 to 1998 in the real world, it may not occur in a model simulation in that year. Over several decades, however, the average number of simulated El Niño events should be similar to those observed. Similarly, although the central U.S. suffered the effects of an unusually intense heat wave during the summer of 1995, model simulations for 1995 might show that year as average or even cooler-than average. However, a similarly intense heat wave should be simulated some time during the climatological period centered around 1995.

In this study, ten different global climate models were used. Their origins, horizontal and vertical resolution, and further references, are provided in Table 2.2 below. These models were chosen based on several criteria. First, only well-established models were considered, those already extensively described and evaluated in the peer-reviewed scientific literature. Models must have been evaluated and shown to adequately reproduce key features of the atmosphere and ocean system. Second, the models had to include the greater part of the IPCC range of uncertainty in climate sensitivity (2 to 4.5°C; IPCC, 2007). Climate sensitivity is defined as the temperature change resulting from a doubling of atmospheric carbon dioxide concentrations relative to pre-industrial times, after the atmosphere has had decades to adjust to the change. In other words, climate sensitivity determines the extent to which temperatures will rise under a given increase in atmospheric concentrations of greenhouse gases (Knutti & Hegerl, 2008). The extent to

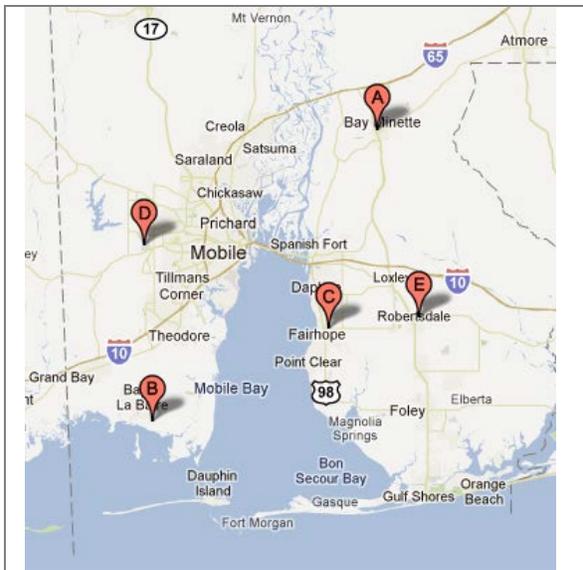


Figure 2.6 Locations of the 5 weather stations surrounding Mobile Bay, Alabama, used in this analysis.

which model uncertainty, including climate sensitivity, affects future projections is discussed further in Section 5. The GCMs used here range from relatively low sensitivity (PCM, 2.1°C) to moderate (GFDL CM2.1, 3.4°C; see Table 2.2).

Few models have climate sensitivity exceeding 4°C and, of those, none had continuous time series available for at least two of the three scenarios used in this analysis. Thus, the third and last criteria is that the models chosen must have continuous daily time series of temperature and precipitation archived for at least two of the three emission scenarios used here (SRES A1fi, A2, and B1). The GCMs selected for this analysis are the

only ten models for which continuous daily output from at least two of the three A1fi, A2 and/or B1 simulations was available.

As GCMs are global, these simulations could be used to evaluate climate impacts anywhere in the world. For some regions of the world (including the Arctic, but not the continental U.S.) there is some evidence that models better able to reproduce regional climate features may produce different future projections (e.g. Overland et al., 2011). Hence, depending on the geographic region it may or may not be desirable to cull models that have been demonstrated in the literature to fail to reproduce important regional climate characteristics (Knutti, 2010). Such characteristics include large-scale circulation features or feedback processes that can be resolved at the scale of a global model. However, it is not valid to evaluate a global model on its ability to reproduce local features, such as the bias in temperature over a given city or region. Such limitations are to be expected in any GCM, as they are primarily the result of a lack of spatial resolution rather than any inherent shortcoming in the physics of the model.

Historical Observations

Station-level observations of daily maximum and minimum temperature and precipitation were obtained from the Global Historical Climatology Network, produced jointly by the U.S. Department of Energy's Carbon Dioxide Information Analysis Center (CDIAC) and the National Oceanographic and Atmospheric Administration's National Climatic Data Center (NCDC; Vose et al., 1992). Five stations surrounding the Mobile Bay region were selected for analysis: (A) Bay-Minette, (B) Coden, (C) Fairhope, (D) Mobile Airport, and (E) Robertsdale, AL (Table 2.3, Fig. 2.6).

Although GHCN station data have already undergone a standardized quality control (Durre et al., 2008), these stations were additionally filtered using a quality control algorithm to identify and remove erroneous values that had previously been identified in

the GHCN database. This additional quality control step included three tests for errors, where any occurrences were removed and replaced with “NA” values. The first error test removed the data on any days where the daily reported minimum temperature exceeds the reported maximum. The second error test removed any temperature values above or below the highest recorded values for North America (-50 to 70°C) or with precipitation below zero or above the highest recorded value for the continental U.S. (915 mm in 24h). The third error test removed repeated values of more than five consecutive days with identical temperature or non-zero precipitation values to the first decimal place.

Station Name	Latitude	Longitude	Beginning of Record		GHCN ID	NOAA CO-OP ID
			Temp	Precip		
(A) Bay-Minette	30.8839	-87.7853	Mar 1915	Nov 1913	USC00010583	10583
(B) Coden	30.3878	-88.2281	Oct 1956	Oct 1956	USC00011803	11803
(C) Fairhope	30.5467	-87.8808	Aug 1917	Aug 1917	USC00012813	12813
(D) Mobile (airport)	30.6883	-88.2456	Jan 1948	Jan 1948	USC00015478	15478
(E) Robertsdale	30.565	-87.7017	Feb 1924	May 1912	USC00016988	16988

Table 2.3. Latitude, longitude, and identification numbers for the 5 weather stations used in this analysis.

The quality control algorithm also flagged (but did not replace) any occurrences of four possible errors: first, years with very low or very high annual temperature ranges; second, decades with mean values greater than 1.5 times the standard deviation of the previous decade; and lastly, years with a number of wet (precipitation>0.1”) or drizzle (precipitation>0”) days exceeding the maximum recorded North American value (350 days).

Downscaling Methods

Global models cannot accurately capture the fine-scale changes experienced at the regional to local scale. GCM simulations require months of computing time, effectively limiting the typical grid cell sizes of the models to 1 or more degrees per side (Table 2.2). And although the models are precise to this scale, they are actually skillful, or accurate, to an even coarser scale (Grotch & MacCracken, 1991).

Dynamical and statistical downscaling represent two complementary ways to incorporate higher-resolution information into GCM simulations. Dynamical downscaling, often referred to as regional climate modeling, uses a limited-area, high-resolution model to simulate physical climate processes at the regional scale, with grid cells typically ranging from 10 to 50km per side. Statistical downscaling models capture historical relationships between large-scale weather features and local climate, and use these to translate future projections down to the scale of any observations—here, individual weather stations.

Regional climate models are just as computationally intensive as global climate models. They also require GCM outputs at high temporal frequencies that are not generally

available. Using currently-available regional climate model simulations, such as those available from the North American Regional Climate Change Assessment Program,³ limits the range of future projections to a few global models and one future scenario that does not capture as broad a range of the uncertainty as that represented here. However, regional models provide a plethora of outputs in addition to temperature and precipitation (including atmospheric circulation, winds, humidity, etc.). Hence, regional model simulations or dynamical downscaling provides essential inputs to sensitivity analyses that require a broad suite of climate variables in order to assess a given system's potential vulnerabilities to changing climate.

Statistical models assume that the relationship between large-scale weather systems and local climate will remain constant over time. This assumption may be valid for lesser amounts of change, but could lead to biases under larger amounts of climate change (Vrac et al., 2007). Statistical models are generally flexible and less computationally-demanding, able to use a broad range of GCM inputs to simulate future changes in temperature and precipitation for a continuous period from 1960 to 2100. Hence, statistical downscaling models are best suited for analyses that require a range of future projections that reflect the uncertainty in emission scenarios and climate sensitivity, at the scale of observations that may already be used for planning purposes.

Ideally, climate impact studies should use multiple downscaling methods, as regional climate models can directly simulate the response of regional climate processes to global change, while statistical models can better remove any biases in simulations relative to observations. However, rarely (if ever) are the resources available to take this approach.

Instead, most assessments tend to rely on one or the other type of downscaling, where the choice based on the needs of the assessment (e.g., Hayhoe et al., 2004, 2008; USGCRP 2000, 2009). If the study is more of a sensitivity analysis, where using one or two future simulations is not a limitation, or if it requires many climate variables as input, and has a generous budget, then regional climate modeling may be more appropriate. If the study needs to resolve the full range of projected changes under multiple GCMs and scenarios, or is more constrained by practical resources, then statistical downscaling may be more appropriate.

Even within statistical downscaling, selecting an appropriate method for any given study depends on the questions being asked. The variety of techniques ranges from a simple delta approach (which consists of subtracting historical simulated values from future values, and adding the resulting "delta" to historical observations, as used in USGCRP, 2000) to complex clustering and neural network techniques that rival dynamical downscaling in their demand for computational resources and high-frequency GCM output (e.g., Vrac et al., 2007; Kostopoulou et al., 2007).

If the timescales of interest are seasonal or annual averages, as often required for ecological analyses, a delta approach can be appropriate. If timescales of weeks to months are required, as for hydrological analyses, then a monthly quantile mapping approach such as the Bias Correction Statistical Downscaling model (BCSD; Maurer & Hidalgo, 2008, as used in Hayhoe et al., 2004, 2008, USGCRP, 2009) is adequate. If

³ <http://www.narccap.ucar.edu/>

daily values are needed, then an approach is required that uses daily information from the GCMs (as used in Hayhoe et al., 2004).

For this analysis, an approach that uses daily GCM output was used, known as the Asynchronous Regional Regression Model (ARRM; Stoner et al., submitted). Asynchronous quantile regression assumes that if two independent time series describe the same variable, at approximately the same location, then they must have similar probability distributions. This is generally a valid assumption for variables such as temperature and precipitation that are directly simulated by global models, but this assumption was tested by validating the statistical model on an independent set of observational data that was not used to train the statistical model and quantifying biases in simulated historical values across the range of the distribution from the 0.1st to the 99.9th quantile. The results of the validation exercise are discussed in detail in Section 5.

A statistical downscaling model, rather than regional climate model output, was selected for use in this study for three reasons. First, this assessment only required projected changes in air temperature and precipitation, both of which can be generated using a statistical model. No additional variables were required. Second, the study required future projections that cover the full range of plausible emission scenarios and GCM simulations. Regional climate model outputs do not yet cover this broad a range of scenario and model uncertainty (see discussion of uncertainty in Section 5). Third, projections were requested for three future time periods: near-term, mid-century, and end-of-century. Regional climate model simulations do not provide continuous time series but are typically limited to only one or two future time slices.

The high-resolution projections used in USGCRP (2009), the upcoming USGS GeoData Portal (2011), and this report are all based on a similar set of global climate model simulations and future scenarios. However, different combinations of statistical downscaling approaches and observational datasets have been used to generate each dataset. Specifically, the BCSD model used in USGCRP (2009) uses a quantile mapping approach that combines monthly GCM outputs with sampling from the historical daily record to produce daily values (Fig. 2.7a). In contrast, the ARRM model used here and in the upcoming USGS GeoData Portal uses a quantile regression technique that directly downscales daily output from global climate models (Fig. 2.7b). Table 2.4 summarizes the similarities and differences between the datasets.

Dataset	Year	GCM simulations	Observed data	Downscaling method
MOBILE	2011	CMIP3	GHCN stations	ARRM
USGS GeoData Portal	2011	CMIP3, CMIP5 (2012)	1/8 th degree grid and GHCN stations	ARRM
USGCRP	2009	CMIP3	1/8 th degree grid	BCSD

Table 2.4 Downscaling methods, observational data, and climate model simulations used to generate three different datasets of high-resolution climate projections.

Asynchronous Regional Regression Model (ARRM)

The ARRM model used in this analysis is based on a highly generalizable quantile regression technique first introduced by Koenker & Basset (1978) to estimate conditional quantile functions by training a model using observational data to describe quantiles of the modelled predictor variable as functions of observed predictand covariates (Koenker & Hallock, 2001). In other words, a quantile regression model is derived for each weather station that transforms dataset A (e.g., historical model simulations) into a probability distribution that closely resembles dataset B (e.g., historical observations). This model can then be used to transform additional datasets (e.g. future model simulations) into probability distributions that continue to reflect the characteristics of dataset B (observations). The general process is illustrated in Figure 2.7(a).

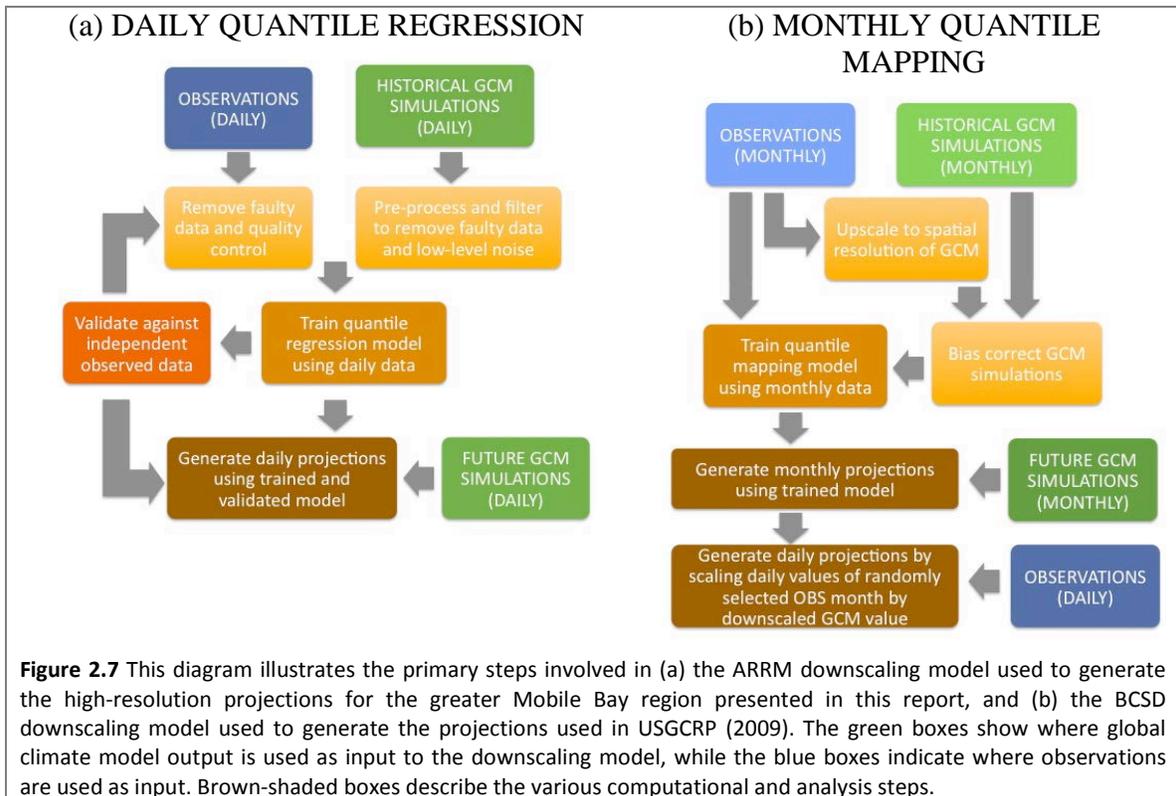
Quantile regression was applied by O'Brien et al. (2001) to calibrate satellite observations from asynchronous, or non-matched, datasets, while Dettinger et al. (2004) was the first to apply this statistical technique to climate projections to examine simulated hydrologic responses to climate variations and change, as well as to heat-related impacts on health (Hayhoe et al., 2004). ARRM expands on these original applications with modifications specifically aimed at improving the ability of the model to simulate the shape of the distribution including the tails, including pre-filtering of GCM input using principal components analysis, use of a piecewise rather than linear regression to accurately capture the often non-linear relationship between modeled and observed quantiles, and bias correction at the tails of the distribution.

Quantile regression has two key advantages relative to other statistical approaches: first, it does not require temporal correspondence between model simulations and observations; and second, it is capable of incorporating model-simulated changes in the shape of the daily distribution (including shifts in the mean, skewedness, and variance) into future projections. In comparison to regional modeling, it is highly efficient, since it does not involve retention of the large-scale dynamical flow patterns, and thus does not require significant computer resources.

Transforming GCM output into high-resolution projections using ARRM begins with daily observations of temperature and precipitation, filtered using a quality control process to remove questionable or erroneous values as described previously. Next, climate model output fields are re-gridded to the scale of the observations using bilinear interpolation. For training, the method requires a minimum of 20 years of observations and model simulations with less than 5% missing data over that time period in order to

produce robust results. For the five stations in this analysis, 51 years or the entire observational record from 1960 to 2010 was utilized for training purposes.

Model predictor values and observed predictand values are ranked and a function (here, a piecewise linear regression) is fitted to the datasets by month, including two weeks of overlapping data on either side. This additional refinement was added to account for shifting seasons in future projections that may produce conditions outside the range of a typical historical month in the future, and allows the method to utilize each data point twice rather than once during the training process.

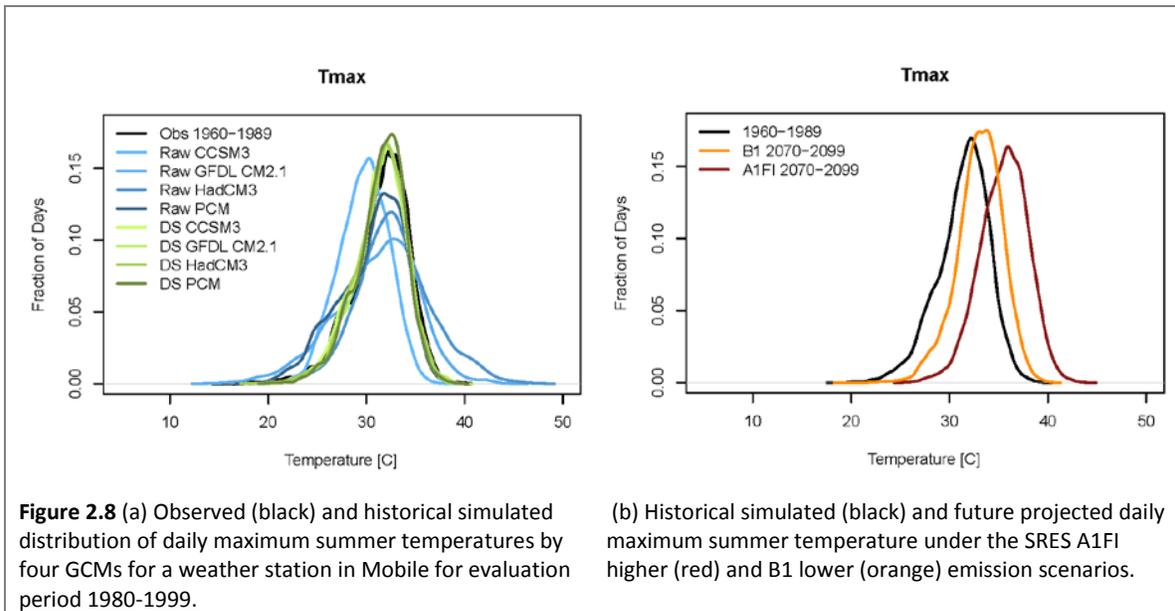


Optimal placements and number of break points (up to six) in the piecewise linear regressions are identified automatically as locations with higher curvature on a plot of ranked modeled vs. observed values. The slopes of the regression segments are checked to ensure no negative slopes are present, and if there is a negative slope a break point is removed to force a positive slope.

Improved performance on temperature downscaling is obtained by filtering the model fields using an empirical orthogonal function (EOF) analysis, also referred to as principal component analysis, that retains only 97% of the original variance. As the linear regressions at the tails are based on a much lower number of data points than those in the center of the distribution, the low and high tail of the distributions undergo further scrutiny by performing bias correction at the tails, ensuring that values are within 30% of the observations.

For precipitation, the model selects from three possible predictors the one best suited to each month: convective, large-scale, or total precipitation. EOF filtering of the model output is not performed since it degrades the results and introduces negative values for precipitation. The logarithm of precipitation values is used instead of raw precipitation amount as this was found to decrease the residuals of the regression.

The downscaling is performed as follows: for each individual station, GCM output for the “training” period, 1960-2010, is regressed on observed daily temperature and precipitation for the same time period to quantify the statistical relationship between each individual quantile of that variable’s daily distribution, and compared to observations (Fig. 2.8a). The statistical relationship derived from the observations and historical GCM simulations is then applied to future GCM simulation output in order to downscale future temperature and precipitation conditions to the same locations used to derive the original regression relationships (Fig. 2.8b). Finally, the validity of the statistical relationship can finally be evaluated through comparison with an independent set of observations that were not used to train the statistical model. Validation of the downscaling for the five Mobile Bay weather stations is summarized in Section 5.



STEP THREE: Translating into impact-relevant information

The final step in the analysis was to translate projected changes in primary climate variables (maximum and minimum temperature and 24h cumulative precipitation) into a series of secondary climate indicators listed in Table 2.1. The results of this translation are described in Sections 3 and 4.

SECTION 3: TEMPERATURE-RELATED CHANGES

Over climate time scales of thirty years or more, average temperature and related indicators in the Mobile Bay region are expected to reflect the multiple influences of global change, modified by local factors including topography, small-scale feedback processes, and land use. The magnitude and rate of global change depends on human emissions of heat-trapping gases, as well as on the sensitivity of the Earth's climate system to those emissions. As global change increases in magnitude, its influence on local-scale climate is likely to grow.

This section summarizes historical observed trends and the changes in temperature and temperature-related secondary indicators that are projected to occur in response to global change. Projected changes are consistent across all five stations; unless otherwise indicated, plotted values correspond to the average value across the five stations.

Annual and Seasonal Temperatures

Historical observed trends in average temperatures vary by month and station. In this analysis, trends were detected using a Mann-Kendall trend analysis. A “significant” trend is defined here as one with a p-value less than 0.1, and a “consistent” trend is one where multiple stations have a significant trend with the same sign of the Kendall τ either negative (decreasing) or positive (increasing).

For average, seasonal, and monthly temperatures there were no historical trends for the period 1960 through 2010 that were significant and consistent across all five stations. When the definition of consistency was relaxed to require only four out of five stations showing a trend in the same direction, negative trends (or cooling) were detected for average minimum temperature for three indicators: monthly values in April and September, and seasonal values for Fall (SON).

Future projections assume that local factors, including topographical influences, changes in land use, and small-scale feedback processes that determine the response of local climate to larger-scale influences, remain invariant. The only factors permitted to change in these future projections are the magnitude of global climate change, and its influence at the regional scale.

⁴ The p-value measures the probability of obtaining a given value in error. A p-value of 0.1, therefore, indicates 90% confidence that the trend detected is real. The Kendall tau shows how a given variable is correlated with time in order to demonstrate whether a trend is present. The sign of tau indicates whether the trend is positive or negative (i.e. increasing or decreasing with time). Tau values can range from -1 to +1, with larger absolute values indicating stronger trends.

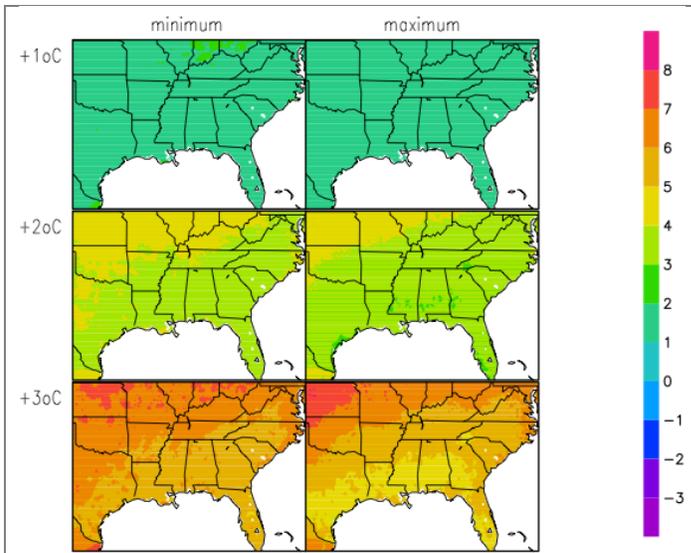


Figure 3.1 Change in Southeast annual average minimum and maximum temperature, in degrees F, projected to occur under global mean temperature increases of 1°C (top), 2°C (middle) and 3°C (bottom). Shown here is the mean value as simulated by the ten climate models used in this analysis. Projected changes for the Mobile Bay region are consistent with the broader changes projected to occur across the Gulf Coast.

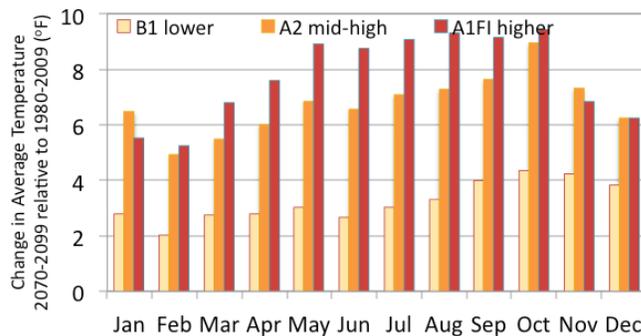


Figure 3.2 Projected change in average monthly temperature for 2070-2099 relative to 1980-2099, in degrees F, for the higher (A1fi), mid-high (A2) and lower (B1) emission scenarios. Values averaged across all climate models and stations.

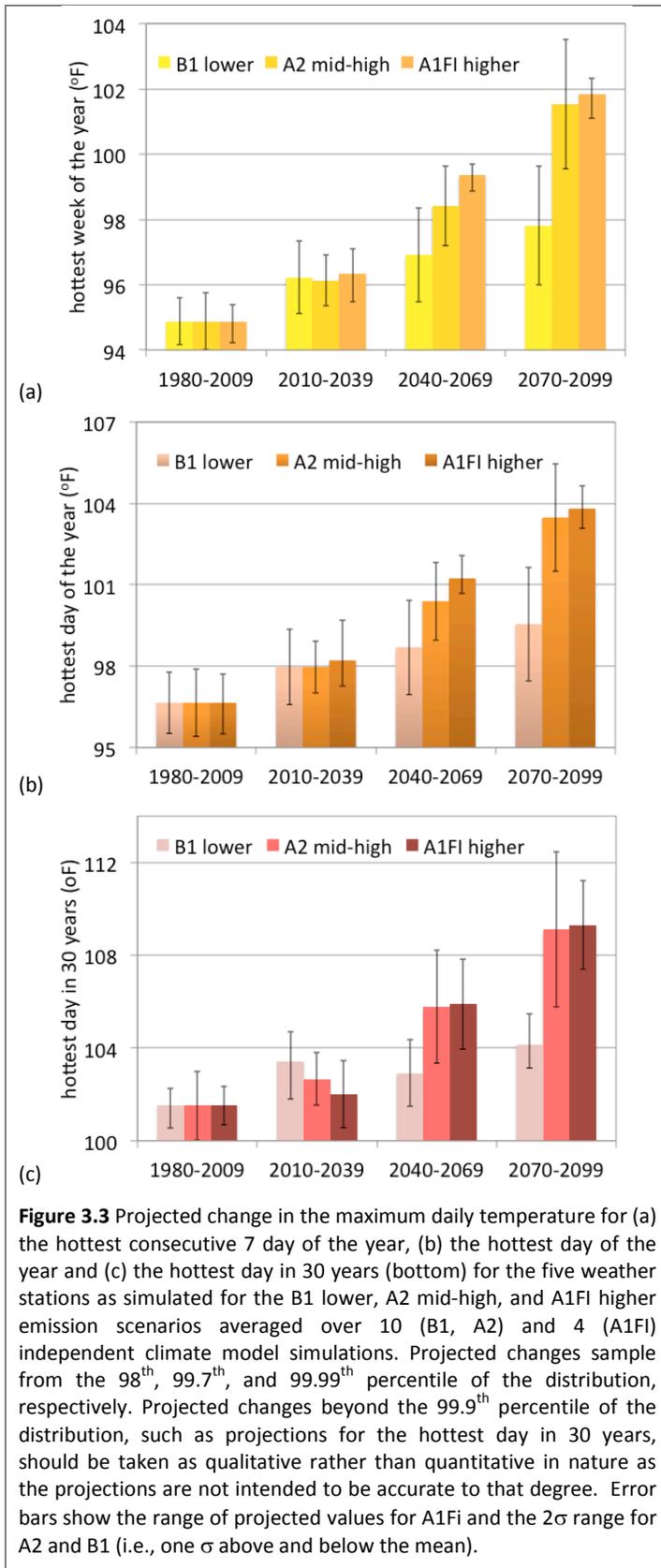
Under these assumptions, annual average temperature is expected to increase in the future. Over the next few decades, projected temperature changes are expected to be similar regardless of the emissions pathway followed over that time (the contribution of scenarios to future uncertainty is discussed further in Section 5). This uniformity arises due to the inherent lag time inherent in the climate system, as well as the lags built into our energy system (i.e., it is unrealistic to consider a scenario where all fossil fuel use could be nearly eliminated within a decade or two). The majority of the changes that will happen over the next few decades are the result of heat-trapping gas emissions that have already built up in the atmosphere or are already entailed by our existing infrastructure (Stott & Kettleborough, 2002).

By 2010-2039, annual temperature is projected to increase by an average of +1.5°F across all scenarios.⁵ By mid-century, increases range from 2.4 to 4.6°F by 2040-2069, depending on the future scenario. By the end of the century (2070-2099), projected increases under higher emissions (+7.7°F) are more than double those expected under

lower emissions (+3.2°F).

Changes in the Mobile Bay region are consistent with those projected to occur across the larger southeastern U.S. and the Gulf Coast (Fig. 3.1). In general, slightly greater changes are projected for minimum as compared to maximum temperature, and for inland as

⁵ In Sections 3 and 4, for the purpose of consistency comparisons across time periods contrast historic *simulated* values with future *simulated* values, and not *observed* or *monitored* data, unless otherwise noted.



compared to coastal regions. Geographic differences likely reflect the moderating influence of the Gulf of Mexico on coastal temperatures.

Both observed and projected future temperature changes vary by season. In the future, over climate timescales of 30 years or more, temperature in all months is projected to increase. Greater warming, on the order of 1°F under lower emissions and more than 2°F under higher emissions by end-of-century, is expected in later summer and fall as compared to other months (Fig. 3.2). The smallest amount of warming is projected in winter months. Under higher emission scenarios, the season of higher warming extends from May through October.

Extreme Heat

For extreme temperature indicators, there were no historical trends for the period 1960 through 2010 that were significant and consistent across all five stations. With the definition of consistency relaxed to require only four out of five stations showing a trend in the same direction, increases were detected in the number of consecutive days per year over 95°F and 100°F. Decreases were observed in the 5th and 25th percentile of warmest consecutive 4 days of the year, as well as in the 50th percentile and mean of the warmest consecutive 7 days.

As mean temperatures increase,

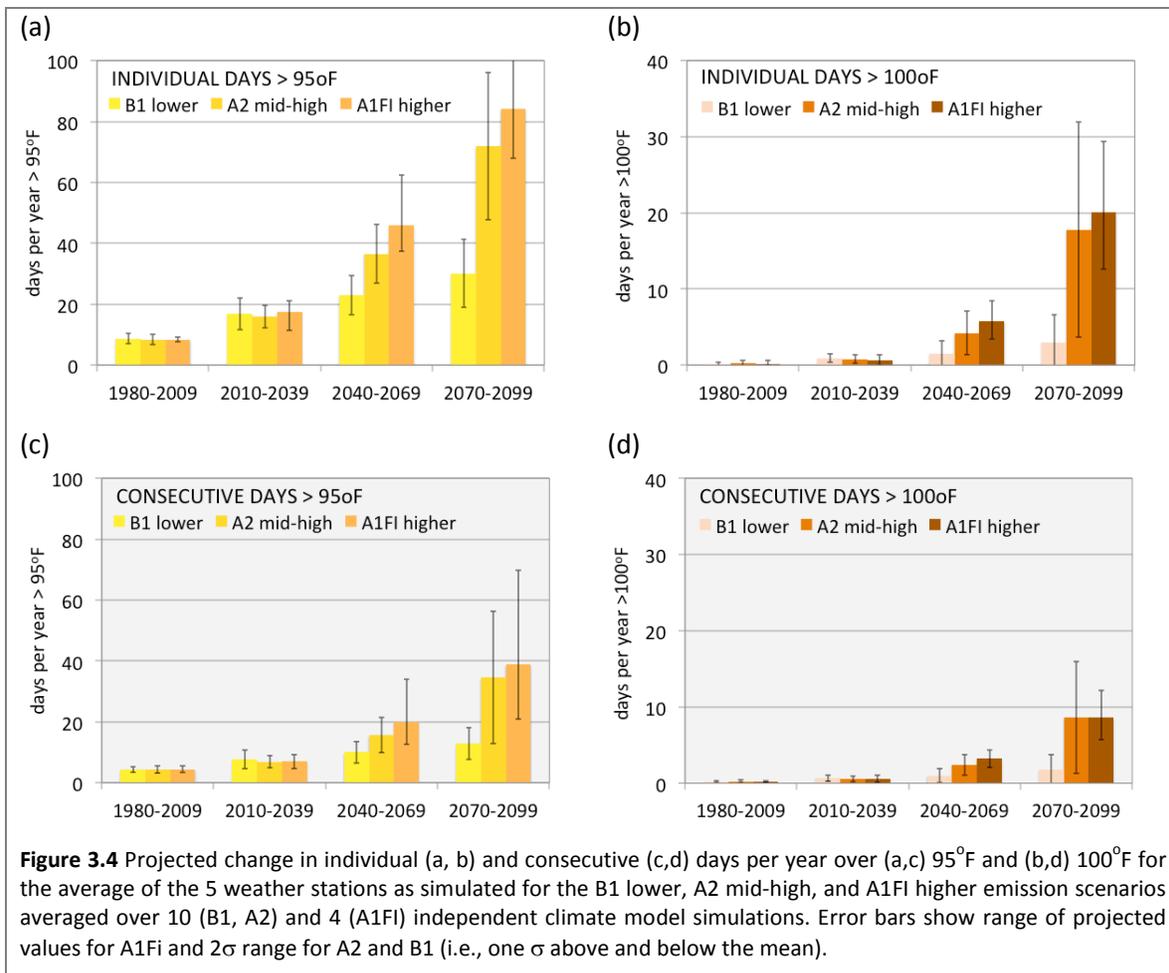
extreme heat is also expected to become more frequent and more severe. Calculations for a large number of heat indices are summarized in the Excel files developed as part of this work. (Note: these are provided as an appendix in the Task 2 report.) Here, representative results from these extreme heat calculations are highlighted, including projected changes in: the hottest day of the year, hottest consecutive 7 days of the year, and hottest day in 30 years or three decades (Figure 3.3), as well as projected changes in the number of days per year over 95 and 100°F (Figure 3.4).

Calculations of the hottest 7 days of the year sample from the 98th percentile of the distribution; the hottest day of the year, the 99.7th percentile; and the hottest day in 30 years, the 99.99th percentile. The degree to which climate simulations are accurate at these percentiles is evaluated in Section 5 using a cross-validation technique to reproduce the historical observations and quantify the biases in simulated vs. observed. In general, however, projected changes beyond the 99.9th percentile of the distribution, such as projections for the hottest day in 30 years, should be taken as qualitative rather than quantitative in nature. The statistics used here to relate regional climate to global-scale change are not intended to be accurate to that scale.

The hottest 7 days of the year historically averages just under 95°F (Figure 3.3a). Within the next few decades, the average temperature of the hottest 7 days of the year is projected to increase by approximately 1.5°F. As indicated by the fact that the average values for each scenario fall within the error bars of the others on the plot, any difference between scenarios over this time scale is purely the result of differences in natural variability between the model simulations. By mid-century, the hottest 7 days of the year are projected to range from 97 to 99°F, with some differences beginning to emerge between scenarios. By the end of the century, average temperature on the hottest 7 days is projected to average 98°F under lower emissions (+3°F relative to the historical period) and almost 102°F under higher emissions (+7°F relative to the historical period), with a statistically significant difference between the values projected under higher vs. lower emissions, as indicated by the fact that the values projected for the mid-high A2 and higher A1FI scenarios lie outside the error bars for the lower B1 scenario. These increases are very similar to those projected for the mean, suggesting that the mean of the distribution could increase at the same rate as the 98th percentile of the distribution.

Sampling from the 99.7th percentile of the distribution, the hottest day of the year for the five weather stations currently averages between 96 and 97°F (Figure 3.3b). This is expected to increase to 98°F by 2010-2039. By 2040-2069, the hottest day of the year is expected to average between 99 and 101°F, depending on emission scenario. By the end of the century, the hottest day of the year could average more than 103°F under higher emissions (+7°F relative to the historical period), or 99°F under lower (+3°F relative to the historical period). Again, the magnitude of this increase is very similar to that projected for the hottest 7 days of the year, and the mean value of the distribution (average annual temperature).

Daily maximum temperature for the hottest day in 30 years currently averages around 101°F. This index is also projected to increase in the future, with some indication of greater changes under higher emission scenarios as compared to lower (Figure 3.3c). Increases are approximately the same magnitude as projected for the hottest day and



week of the year; however, these type of climate projections are not intended to be accurate to the one-in-10,950th day or the 99.99th percentile of the distribution. Hence, these results should be interpreted cautiously, with greater emphasis on qualitative direction of trends rather than quantitative numbers.

Temperature thresholds also show increases in the number of days per year exceeding a given value. Projections were requested for number of days exceeding 95, 100, 105 and 110°F, as well as for the maximum number of consecutive days exceeding those thresholds. For all five weather station locations, there are currently no days per year over 105°F and no significant changes in this number are projected for the future; hence, only projections for days over 95 and 100°F are shown here.

On average, the Mobile Bay region currently experiences between 8 to 9 days per year above 95°F, with 4 to 5 or just over half of those days occurring during one single consecutive period (i.e., during a heat wave) and very few days per year over 100°F (Fig 3.4).⁶ The average number of consecutive days per year over both 95 and 100°F already

⁶ Unless otherwise indicated, all figures compare model-based historical with future simulations. After downscaling, the average statistics of simulated climate for 1980 – 2009 are nearly identical to observed data but may not match precisely because global climate models represent slightly different samples or subsets of all possible combinations of the natural variability that could have occurred during that period.

show significant trends from 1960 through 2010. As average temperatures increase, the number of days per year over 95°F is projected to increase, as is the number of consecutive days. Projections of nearly 40 consecutive days over 95°F under higher emissions and 13 consecutive days under lower emissions suggest that heat waves, if defined as occurring when maximum daily temperatures exceed 95°F, could increase in length by as much as a factor of 10 under a higher emissions scenario, and 3 under a lower scenario. The number of individual days per year is projected to be approximately twice the number of consecutive days.

Days with maximum temperature exceeding 100°F are currently rare (the hottest day on record in Mobile, AL is 105°F in 2000). Within the next few decades, several such days are expected each year. By mid-century, between 1.5 and 6 days per year could be over 100°F, depending on the emission scenario. By the end of the century, an average of 3 individual days and 2 consecutive days per year over 100°F are projected under lower emissions and up to 20 individual days or 8 consecutive days per year under higher emissions. The analysis for days over 100°F samples from the far tail of the distribution of daily temperature so projections are less robust than for less extreme temperature thresholds.

Cold Temperatures

For extreme cold temperature indicators, there were no historical trends in the indicators requested for the period 1960 through 2010 that were significant and consistent across all five stations.

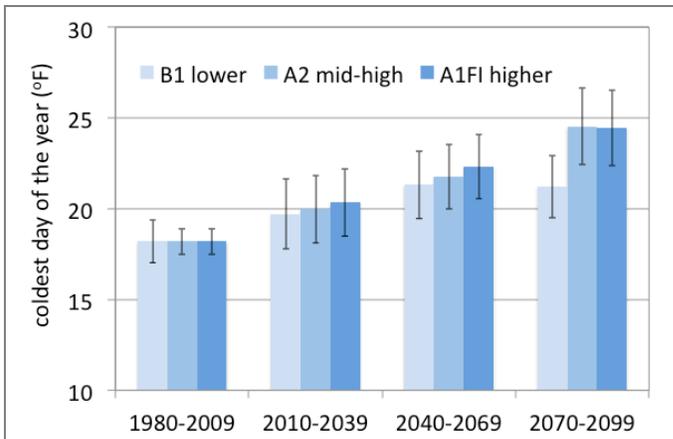


Figure 3.5 Projected change in the temperature of the coldest day of the year (or the 99.7th percentile of the distribution of minimum temperature) for Mobile, AL as simulated for the B1 lower, A2 mid-high, and A1FI higher emission scenarios averaged over 10 (B1, A2) and 4 (A1FI) independent climate model simulations. Error bars show range of projected values for A1FI and 2σ range for A2 & B1 (i.e., one σ above and below the mean).

As average temperatures increase, however, cold temperatures are also expected to become less frequent and less severe. For example, the temperature of the coldest day of the year (currently 18°F, which is the 99.7th percentile of the distribution) is expected to increase by +2°F, to 20°F, within the next few decades, and by an average of +3-4°F, to 21-22°F, by mid-century (Fig. 3.5). By the end of the century, there is some difference between the expected temperatures under lower emissions (21°F) as compared to higher (24.5°F, or an increase of 6.5°F compared to historical).

Average winter temperatures are projected to increase across the distribution, from the 5 to 95th percentile, by an average of 5-6°F under the higher A1fi and mid-high A2 scenarios, and 3°F under the lower B1 scenario by the end of the century. The contribution of scenarios to overall uncertainty is discussed further in Section 5.

SECTION 4: CHANGES IN PRECIPITATION

Climate change is not just about warmer temperatures; as the planet warms, precipitation patterns are also expected to shift in both space and time. Some seasons may get wetter, while others get drier. The intensity and frequency of heavy rainfalls, as well as the duration of dry periods, may be altered.

This section summarizes observed historical trends and the changes in precipitation and rainfall-related secondary indicators that have been observed and are projected to occur in the Mobile Bay area in response to global change. As in Section 3, historical trends were detected using a Mann-Kendall trend analysis. A “significant” trend is defined here as one with a p-value less than 0.1, and a “consistent” trend is one where multiple stations have the same sign of the Kendall τ . Projected future changes are consistent across all five stations; unless otherwise indicated, plotted values correspond to the average value across the five stations.

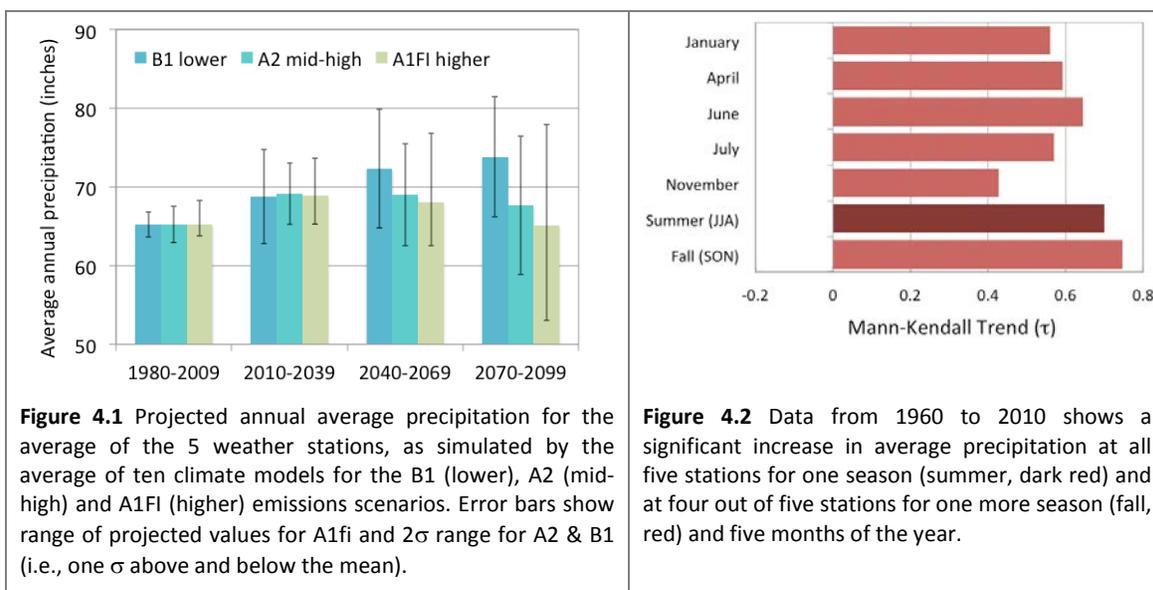
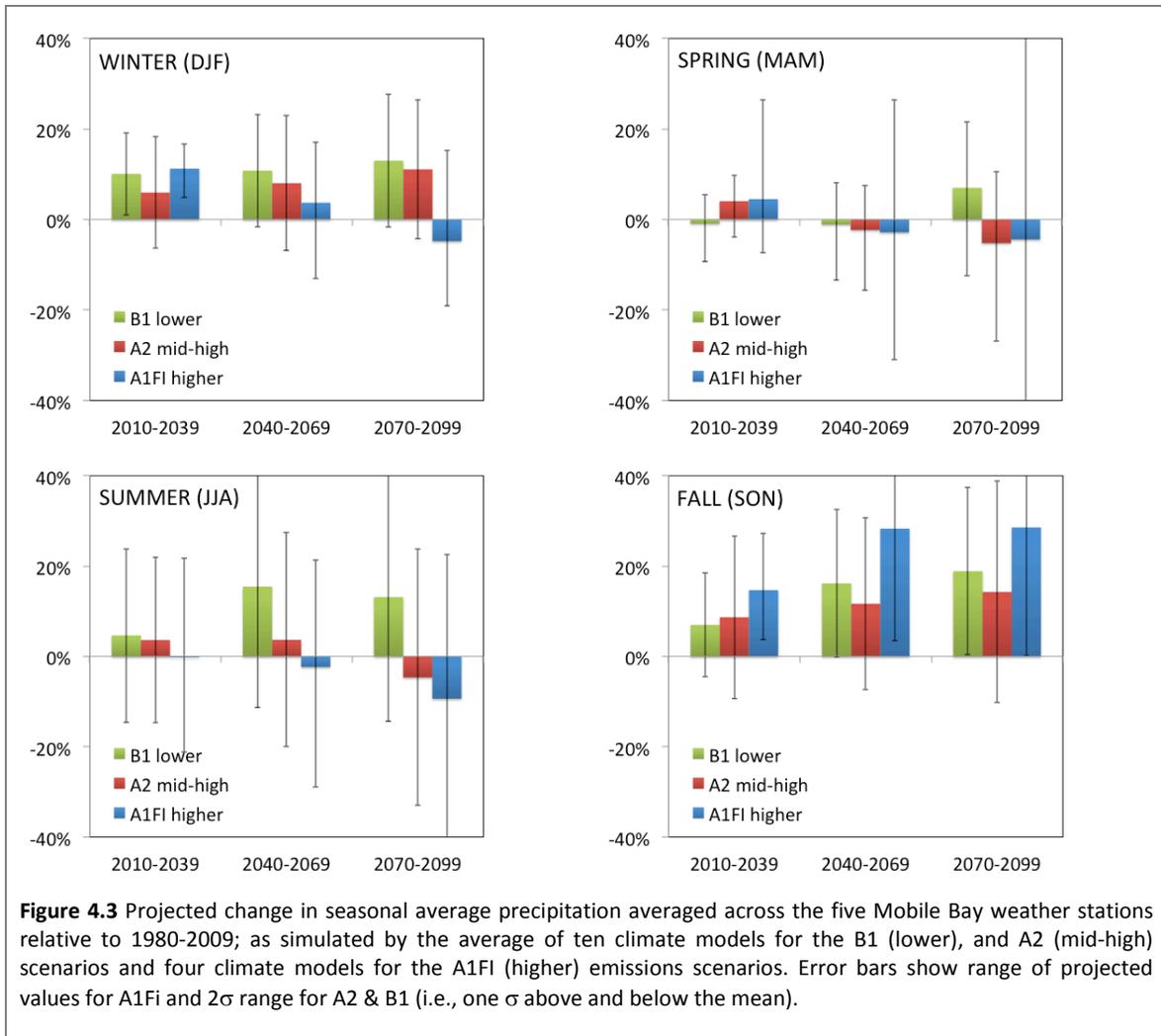


Figure 4.1 Projected annual average precipitation for the average of the 5 weather stations, as simulated by the average of ten climate models for the B1 (lower), A2 (mid-high) and A1FI (higher) emissions scenarios. Error bars show range of projected values for A1fi and 2σ range for A2 & B1 (i.e., one σ above and below the mean).

Figure 4.2 Data from 1960 to 2010 shows a significant increase in average precipitation at all five stations for one season (summer, dark red) and at four out of five stations for one more season (fall, red) and five months of the year.

⁷ The p-value measures the probability of obtaining a given value in error. A p-value of 0.1, therefore, indicates 90% confidence that the trend detected is real. The Kendall tau shows how a given variable is correlated with time in order to demonstrate whether a trend is present. The sign of tau indicates whether the trend is positive or negative (i.e. increasing or decreasing with time). Tau values can range from -1 to +1, with larger absolute values indicating stronger trends.



Annual and Seasonal Precipitation

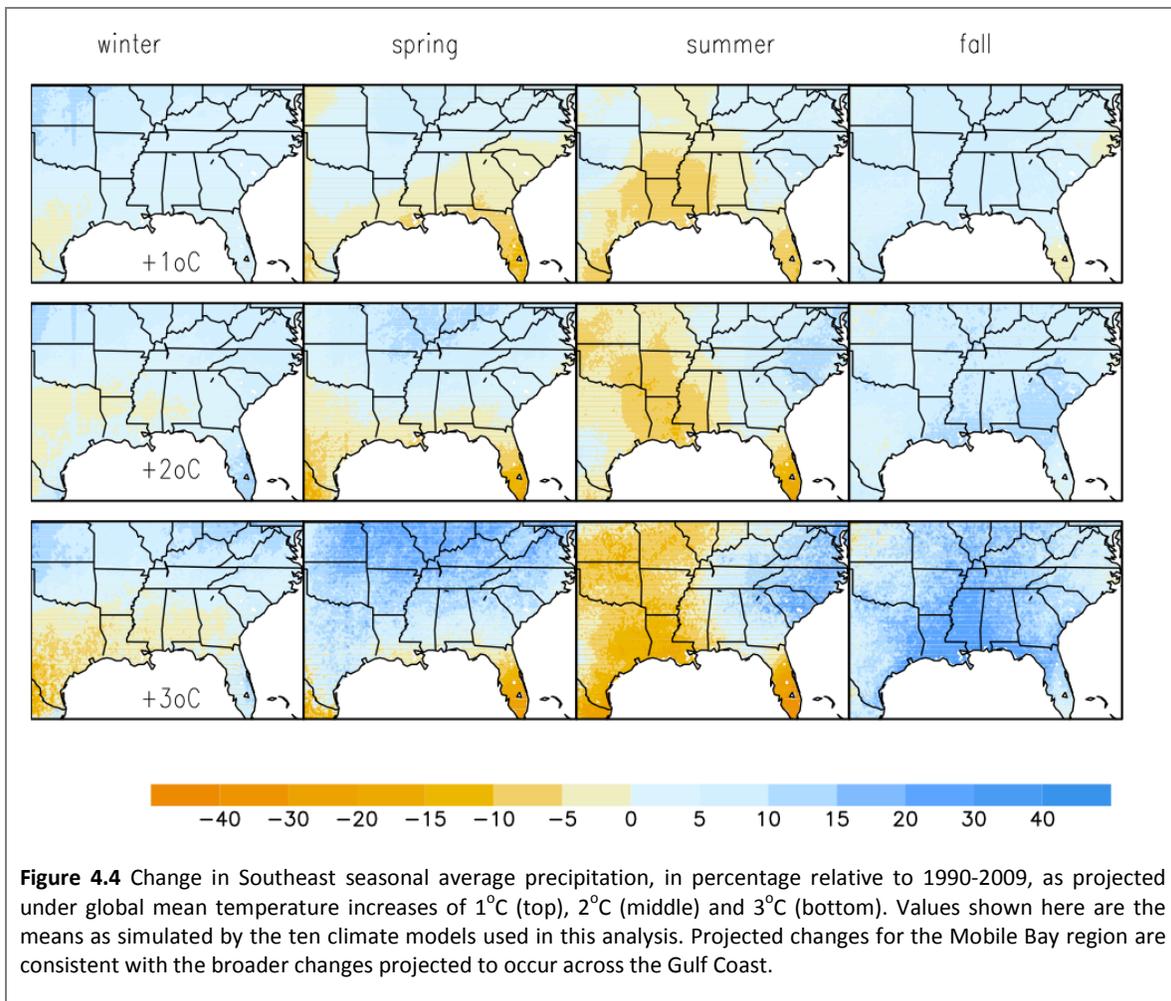
Annual precipitation in the Mobile Bay region averages around 65 inches per year. From 1960 through 2010, no significant changes were observed in this annual average. Over this century, there is some indication, although with significant variability, of a relatively small increase of several inches by mid-century, followed by a return to present-day values under higher emissions scenarios by end-of-century (Fig. 4.1).

Little to no change in annual average precipitation can mask significant changes in the seasonal and monthly distribution of precipitation. From 1960 to 2010, for example, a significant and consistent increase in summer (JJA) precipitation was observed across all five stations. When the definition of consistency was relaxed to require just four out of five stations to show a trend in the same direction, there were significant increases in summer (JJA) and fall (SON) precipitation, as well as monthly average precipitation for January, April, June, July and November (Fig 4.2).

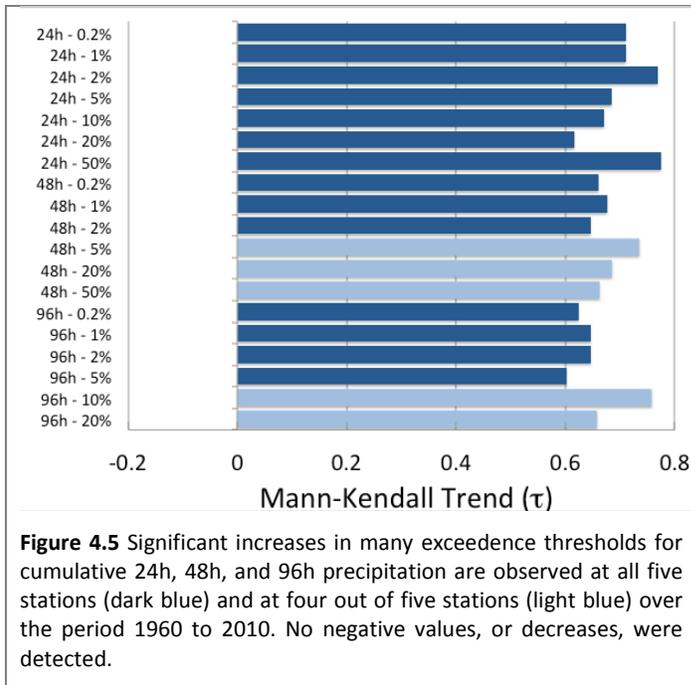
In terms of future projections, fall precipitation continues to show the strongest and most consistent increase across all time periods and scenarios, by up to 30% by end-of-century under higher emissions averaged across all five weather stations. This suggests that the

climate models may be accurately capturing the regional factors responsible for observed increases in fall precipitation over the last 50 years. There is also some indication that precipitation may increase in winter, particularly over the near term and under lower emissions. Projections for the spring and summer, however, have large error bars indicating lack of inter-model agreement regarding the magnitude and even the sign of the change (Fig. 4.3).

Seasonal changes in precipitation in the Mobile Bay region are consistent with those projected to occur across the southeastern U.S. and the Gulf Coast (Figure 4.4). Precipitation changes are largest and most consistent during the fall season; winter shows a slight increase under lower amounts of change; changes in spring are inconsistent; and summer shows risk of drying that increases over time and with larger global change. Uncertainties in these projections are discussed further in Section 5.



Heavy Precipitation Events



Heavy rainfall events can damage homes, businesses, and public infrastructure. The frequency of occurrence of more than 2 inches of rain in 24h, for example, has already increased across much of the U.S., particularly in the Northeast and Midwest (USGCRP, 2009).

In the Mobile Bay region, exceedence thresholds for 24h annual maximum daily precipitation, as well as cumulative 48h and 96h precipitation, show the most significant and consistent changes from 1960 to 2010. For the maximum 24h precipitation, increases in all the exceedence

probabilities from 0.2 to 50% are significant and consistent across all 5 weather stations. For 48h precipitation, increases up to the 5% exceedence are consistent across all stations, and increases in exceedences up to 50% are consistent across four out of the 5 stations. Similar increases are also seen in 96h precipitation (Fig. 4.5).

In many regions, the observed trend in heavy rainfall is expected to continue in the future as warming temperatures accelerate the hydrological cycle at both the local and global scale (e.g. Tebaldi et al., 2006). Here, projected changes in heavy rainfall events are captured by calculating the exceedence thresholds for the 24h annual maximum and cumulative 2-day and 4-day precipitation from the 0.2nd to the 50th quantile, and the maximum 3-day precipitation totals for each season.

This section focuses on projected changes in the 1st and 50th exceedence thresholds for annual maximum 24h precipitation and cumulative 96h precipitation, as representative of the range of changes generally projected for all precipitation indicators. These two metrics not only average precipitation over a different number of hours, but are also defined slightly differently. Exceedance thresholds discussed here are taken from four distinct 30-year datasets and should not be compared with recurrence intervals usually applied to much larger observed historical datasets. Details regarding the calculations methods used for each metric are provided in the Appendix. Additional projections for the complete set of indicators are available in an Appendix to the Task 2 report.

Most precipitation exceedence thresholds are projected to increase, consistent with observed historical trends. There is some indication of slightly greater increases for shorter duration events, but there is also greater uncertainty in the statistics for these shorter events (Figure 4.6). In general, however, most projections show little difference across scenario, rainfall event duration (24, 48, or 96h), or time period (near-term, mid-century, and end-of-century).

Observed cumulative 24h precipitation for the 5 Mobile Bay weather stations averages around 13.5” for the first percentile and 5” for the 50th percentile. Historical simulated values are slightly lower, averaging 12.5” and 4.5” (a further discussion of biases in simulated historical values is provided in Section 5). Consistent with historical trends, increases in the 1st percentile are projected to continue across all scenarios, all models, and for all future time periods (Fig. 4.6a). There is no real difference between the changes projected to occur under any given scenario, or even for any given time period. Thus, rather than showing as a linear trend, these projections suggest more of a “step”-type increase in the exceedence threshold of the 1st percentile. Similarly, exceedence thresholds for the 50th percentile of 24h precipitation are also projected to increase, although changes are less significant compared to historical values. Again, there is little difference between the changes projected under any given scenario or even for any given time period (Fig. 4.6b).

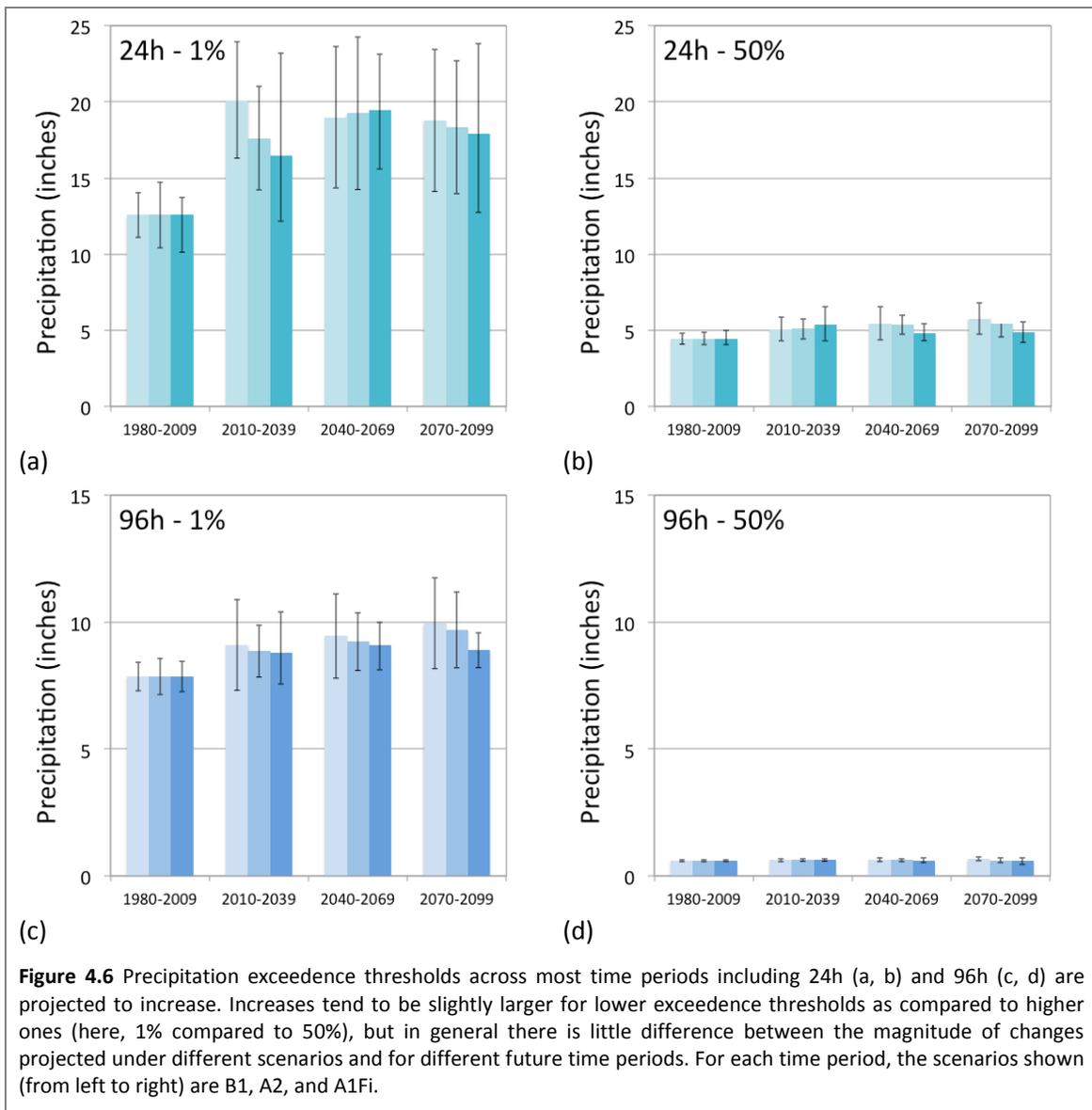


Figure 4.6 Precipitation exceedence thresholds across most time periods including 24h (a, b) and 96h (c, d) are projected to increase. Increases tend to be slightly larger for lower exceedence thresholds as compared to higher ones (here, 1% compared to 50%), but in general there is little difference between the magnitude of changes projected under different scenarios and for different future time periods. For each time period, the scenarios shown (from left to right) are B1, A2, and A1Fi.

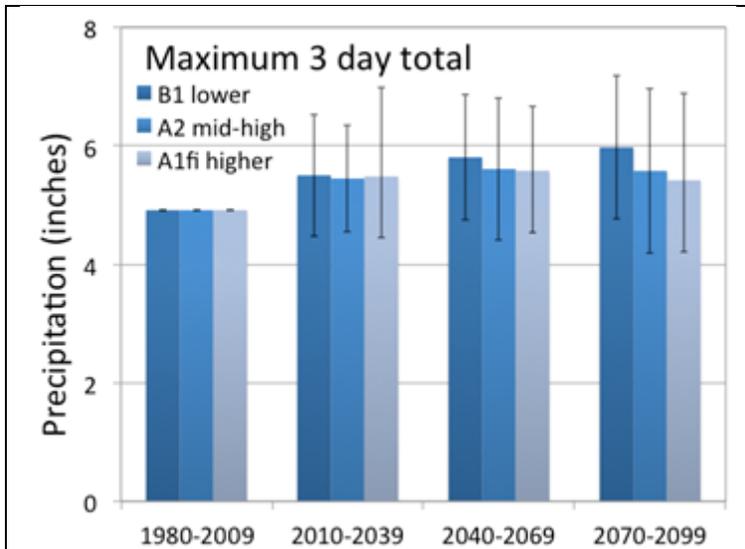


Figure 4.7 Maximum three-day precipitation totals currently average around 5 inches per year. As is the case for the other measures of accumulated precipitation shown in Figure 4.6, projections indicate a likely increase in average values of maximum three-day accumulated precipitation, with little distinction between the changes projected under different scenarios or time periods.

Observed cumulative 96h or 4-day precipitation for the 5 Mobile Bay weather stations averages around 7” for the first percentile and 0.65” for the 50th percentile⁸. Historical simulated values are similar, averaging 8” and 0.6” (a further discussion of biases in simulated historical values is provided in Section 5). Also consistent with historical trends, increases in the 1st percentile are projected to continue across all scenarios, all models, and for all future time periods (Fig. 4.6c). Exceedence thresholds for the 50th percentile of 24h precipitation are also projected to increase slightly,

although changes are less significant compared to historical values (Fig 4.6d). As seen for 24h precipitation, there is little difference between the changes projected under any given scenario or even for any given time period, suggesting that the primary driver of uncertainty in projected future changes in precipitation is scientific or model uncertainty (see Section 5 for more discussion on uncertainty).

Average annual maximum three-day precipitation totals were calculated individually for each season. Historical and simulated future annual average values are shown in Figure 4.7. Projected changes are generally positive, although relatively small (averaging less than 1 inch compared to the historical average of 5 inches). Every season shows some indication of an overall increase in the amount of precipitation accumulated during three-day events. However, in most cases the range of projected values includes the potential for no change or even a slight decrease compared to historical simulated values. Seasonal values (not shown, but available in the excel data files accompanying this report) show increases typically on the order of half an inch in spring and summer, and one inch in winter and fall, also with little difference between emission scenarios and time period.

⁸ Note that this is a four-day running total, and thus is not directly comparable to the 24 hour data.

SECTION 5: UNCERTAINTY

There is always some degree of uncertainty inherent to any future projections. In order to accurately interpret and apply future projections for planning purposes, it is essential to quantify both the magnitude of the uncertainty as well as the reasons for its existence. Each of the steps involved in generating projections—future scenarios, global modeling, and downscaling—introduces a degree of uncertainty into future projections; how to address this uncertainty is the focus of this section.

It is a well-used axiom that all models are wrong (but some can be useful). The Earth's climate is a complex system. It is only possible to simulate those processes that have been observed and documented. Clearly, there are other feedbacks and forcing factors at work that have yet to be documented. Hence, it is a common tendency to assign most of the range in future projections to model, or scientific, uncertainty.

Future projections will always be limited by scientific understanding of the system being predicted. However, there are other important sources of uncertainty that must be considered; some that can even outweigh model uncertainty for certain variables and time scales.

Sources of Uncertainty in Global and Regional Climate Change

Uncertainty in climate change at the global to regional scale arises primarily due to three different causes: (1) natural variability in the climate system, (2) scientific uncertainty in predicting the response of the Earth's climate system to human-induced change, and (3) socio-economic or scenario uncertainty in predicting future energy choices and hence emissions of heat-trapping gases (Hawkins & Sutton, 2009).

It is important to note that scenario uncertainty is very different, and entirely distinct, from scientific uncertainty in at least two important ways. First, while scientific uncertainty can be reduced through coordinated observational programs and improved physical modeling, scenario uncertainty arises due to our fundamental inability to predict future changes in human behaviour. Scenario uncertainty can only be reduced by the passing of time, as certain choices (such as depletion of a non-renewable resource or implementation of an emissions control policy) eliminate or render certain options less likely. Second, scientific uncertainty is often characterized by a normal distribution, where the mean value is more likely than the outliers. Scenario uncertainty, however, hinges primarily on whether or not the primary emitters of heat-trapping gases, including traditionally large emitters such as the United States as well as nations with rapidly-growing contributions such as India and China, will enact binding legislation to reduce their emissions or not. There is no reason *per se* to assume a mid-range scenario is the most likely. For example, if these nations do enact legislation, then the lower emission

scenarios become more probable. If they do not, then the higher scenarios become more probable. The longer such action is delayed, the less likely it becomes to achieve a lower, as compared to a mid-low, scenario because of the carbon dioxide that continues to accumulate in the atmosphere. Hence, scenario uncertainty cannot be considered to be a normal distribution. Rather, the consequences of a lower vs. a higher emissions scenario must be considered independently, in order to isolate the role that human choices are likely to play in determining future impacts.

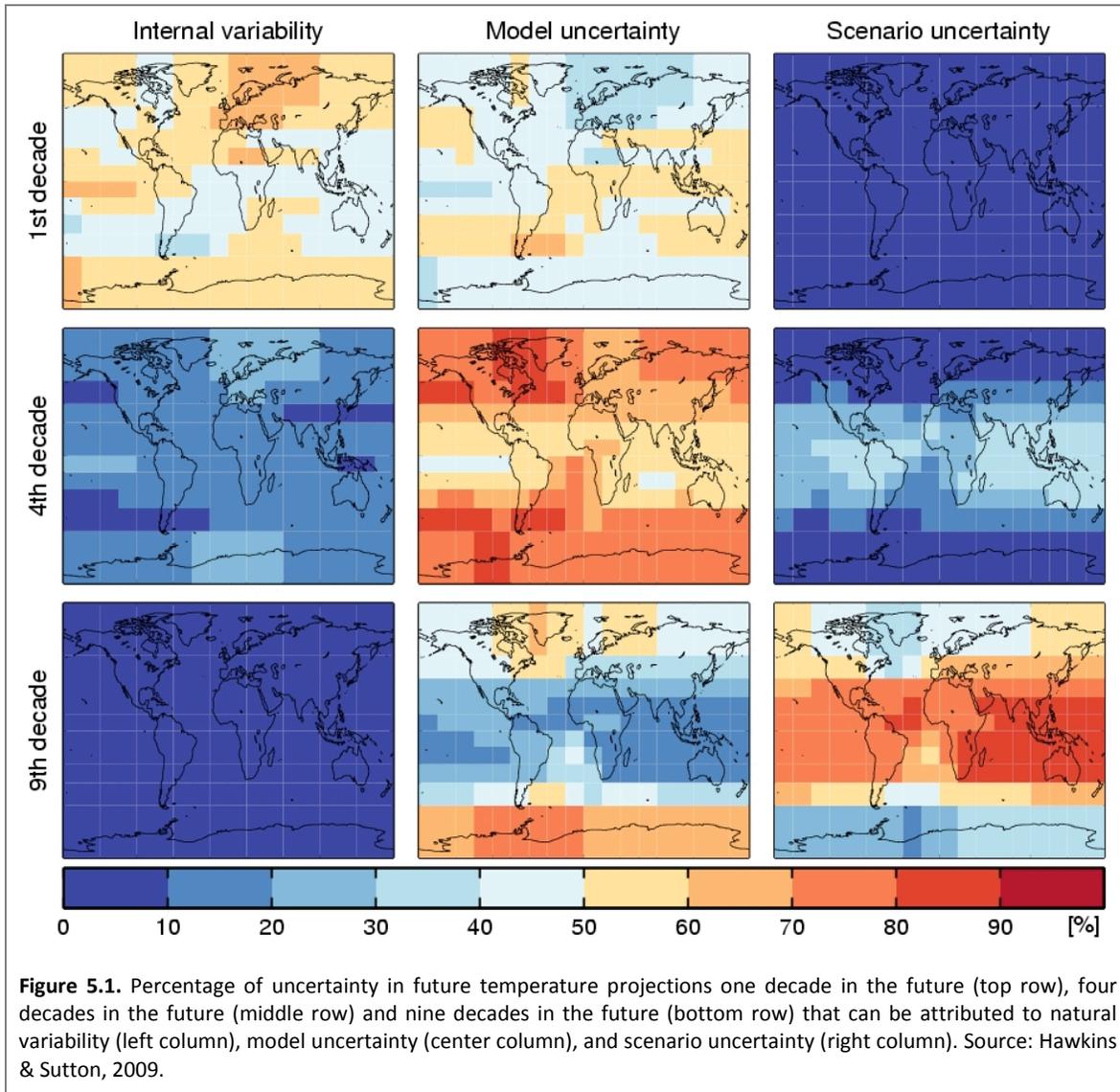


Figure 5.1 illustrates how, over timescales of years to several decades, natural chaotic variability is the most important source of uncertainty. By mid-century, scientific or model uncertainty is the largest contributor to the range in projected temperature and precipitation change. By the end of the century, scenario uncertainty is most important for temperature projections, while model uncertainty continues as the dominant source of uncertainty in precipitation. This is consistent with the results of the projections for the Mobile Bay region discussed in this report, where there is a significant difference

between the changes projected under higher vs. lower scenarios for temperature-based metrics, but little difference for precipitation-based metrics.

Dealing with Uncertainty

The first source of uncertainty can be addressed by always averaging or otherwise sampling from the statistical distribution of future projections over a climatological period – typically, 20 to 30 years. In other words, the average winter temperature should be averaged over several decades, as should the coldest day of the year. No time stamp more precise than 20 to 30 years should ever be assigned to any future projection. In this report and accompanying data files, simulations are always averaged over four 30-year climatological time periods: historical (1980-2009), near-term (2010-2039), mid-century (2040-2069) and end-of-century (2070-2099).

The second source of uncertainty, model or scientific uncertainty, can be addressed by using multiple global climate models to simulate the response of the climate system to human-induced change (here, 10 models for the B1 and A2 scenarios, 4 models for A1FI as that is all that were available at the time of publication). As noted above, the climate models used here cover a range of climate sensitivity; they also cover an even wider range of precipitation projections, particularly at the local to regional scale.

Again, while no model is perfect, most models are useful. Only models that demonstratively fail to reproduce the basic features of large-scale climate dynamics (e.g., the Jet Stream or El Niño) should be eliminated from consideration, as multiple studies have convincingly demonstrated that the average of an ensemble of simulations from a range of climate models (even ones of varied ability) is generally closer to reality than the simulations from one individual model, even one deemed “good” when evaluated on its performance over a given region (e.g., Weigel et al., 2010; Knutti, 2010). Hence, wherever possible, impacts should be summarized in terms of the values resulting from multiple climate models while uncertainty estimates can be derived from the range or variance in model projections. This is why most plots in this report show both multi-model mean values as well as a range of uncertainty around each value.

The third and final primary source of uncertainty in future projections can be addressed through generating climate projections for multiple futures: for example, a “higher emissions” future where the world continues to depend on fossil fuels as the primary energy source (SRES A1FI, A2), as compared to a “lower emissions” future focusing on sustainability and conservation (SRES B1).

Over the next 2 to 3 decades, projections can be averaged across scenarios as there is no significant difference between scenarios over that time frame due to the inertia of the climate system in responding to changes in heat-trapping gas levels in the atmosphere (Stott & Kettleborough, 2002). Past mid-century, however, projections should never be averaged across scenarios; rather, the difference in impacts resulting from a higher as compared to a lower scenario should always be clearly delineated. That is why, in this report, future projections for mid-century and beyond are always summarized in terms of what is expected for each scenario individually.

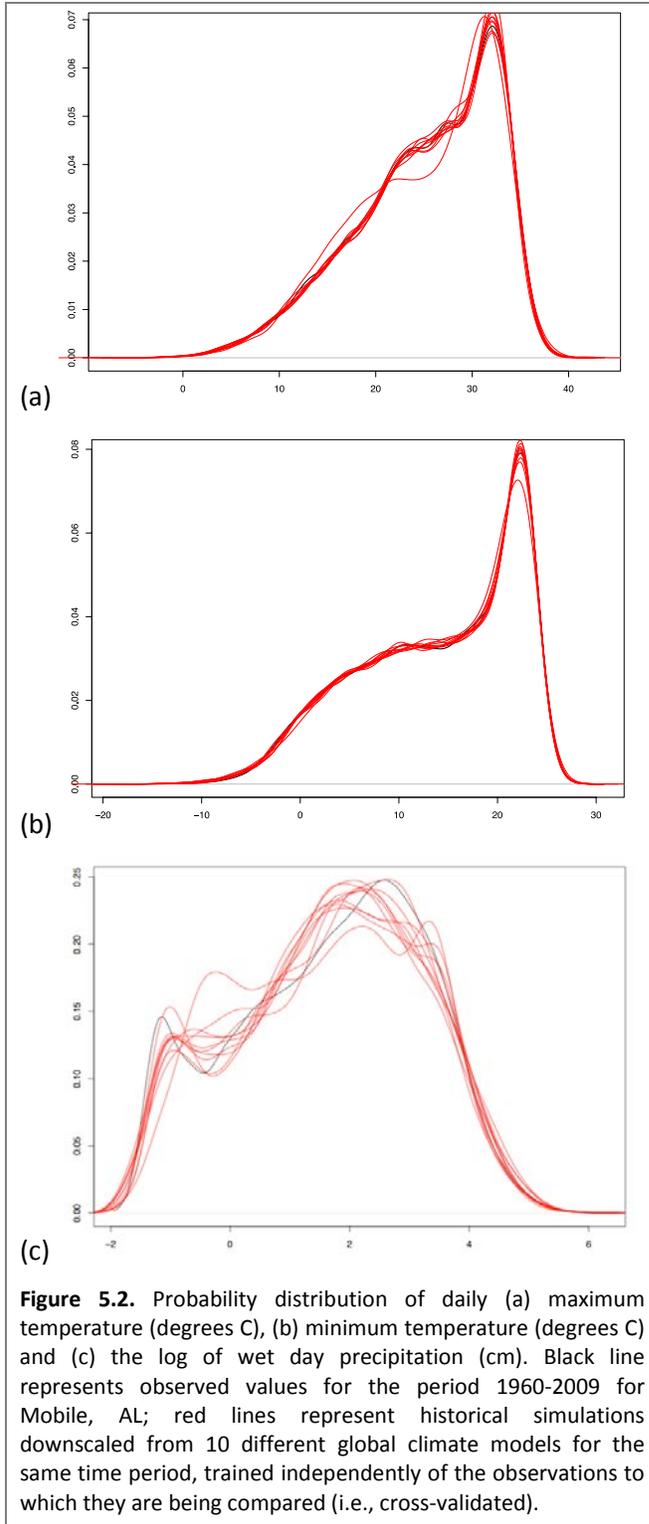
Uncertainty and Bias in Downscaling

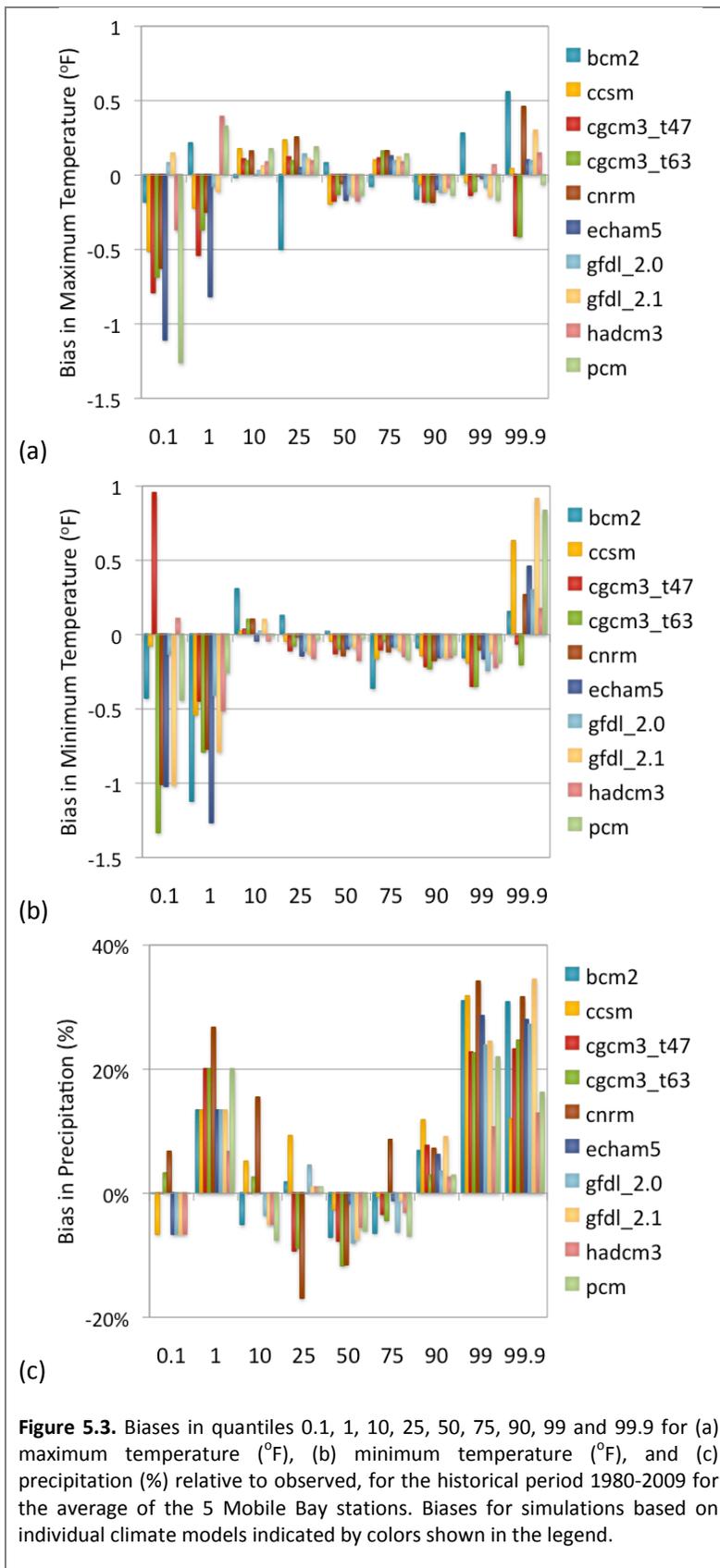
Downscaling climate projections from global models to the scale of individual weather stations introduces a fourth source of uncertainty, that of the downscaling model used to relate large-scale weather patterns to local-scale variability. For a statistical downscaling model, this uncertainty in turn can be

attributed to three distinct sources: (1) the degree to which the limited set of observations used to train the statistical method fail to capture the larger range in possible weather conditions at that location; (2) the inability of the statistical model to perfectly reproduce the relationship between large-scale weather and local conditions; and (3) limitations in the ability of the global climate model to simulate regional conditions.

The extent to which these three sources of uncertainty and error affect the accuracy of local-scale projections can be evaluated through a cross-validation process. Typically, a statistical downscaling model is trained on all available historical data in order to maximize the sample of naturally-occurring weather conditions. The trained model is then used to downscale future simulations using the relationship it has developed between large-scale climate and local weather conditions during the historical period.

During cross-validation, however, the statistical model is trained on all but one year of the historical observations (e.g., 1961-2009), and then used to downscale that single year (1960). This produces one year's worth of simulated historical conditions that are entirely independent of the data used to train the model.





The model is then trained on the years 1960 and 1962-2009 (leaving out 1961) and used to downscale the single year 1961. There are now two years' worth of simulated historical values that are independent of the data used to train the model. This process can be repeated N times, where N is equal to the number of years available in the observational record. The end result is a timeseries of daily simulated variables equal in length, but independent of, the observed record used to train the downscaling method.

The probability, or density, distribution of this cross-validated independent time series can be directly compared to observed maximum and minimum temperature and wet-day precipitation. This comparison is shown in Fig. 5.2. Black lines are observations, while red lines represent the various global models that have been downscaled to the Mobile Airport station.

This comparison shows that simulated maximum & minimum temperature tends to match observed values more closely than wet-day precipitation. It also shows how one or two of the 10 global climate

models used in this analysis (individual models indicated by red curves) tend to be outliers, incapable of reproducing the distribution of local temperature or precipitation to the same degree as the majority of the models.

The cross-validated simulations can also be used to quantify the bias in various quantiles of the distribution of daily climate variables introduced by the downscaling, by essentially ‘slicing’ the distribution at the quantile of interest. Comparing the bias across various global climate models helps to illustrate the component of this error that is due to limitations in the global climate model that the downscaling method is unable to correct for. In other words, a good downscaling model can convert most global climate model simulations into something resembling observations; but its ability is naturally limited by the quality of the input fields from the global model.

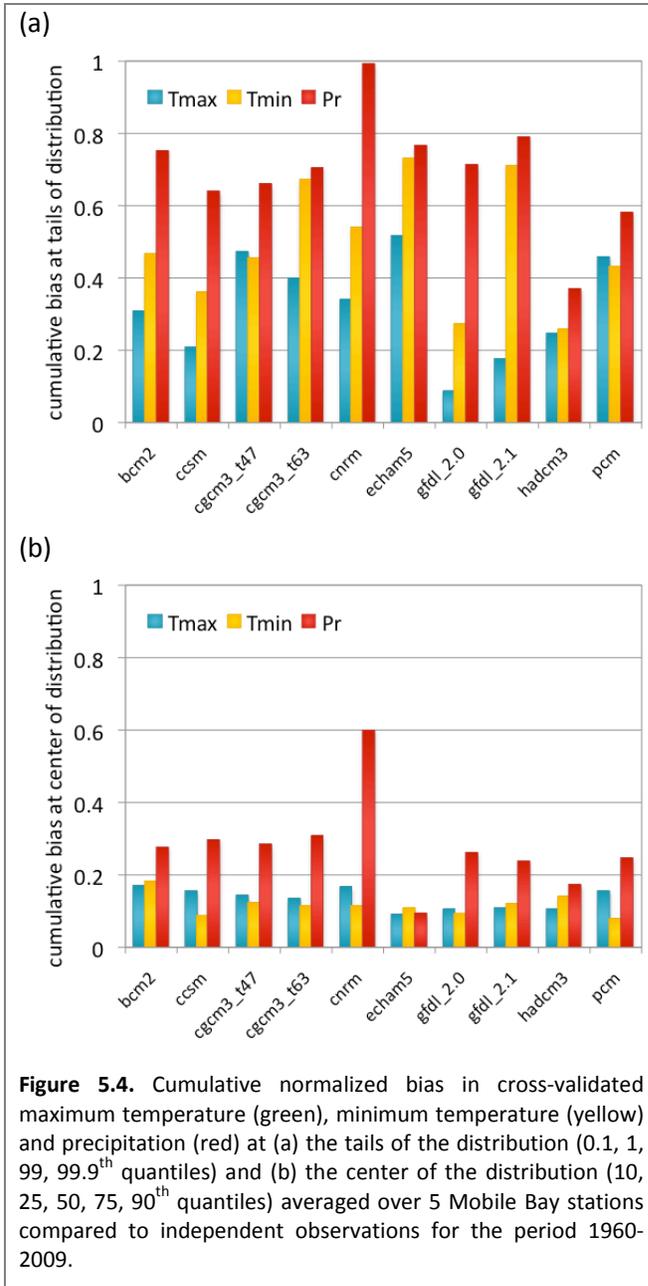
As illustrated in Figure 5.3, absolute biases towards the ends of the temperature distribution (0.1 and 99.9th quantiles) tend to be much greater than the biases for quantiles towards the center of the distribution. This reflects the fact that there is much less observational data available to train the model at the tails of the distribution as compared to the center. For temperature, biases at the ends of the distribution can be as great as +/- 1°F; whereas biases in the center tend to average around +/-0.2°F. Biases also tend to be higher for T_{min} as compared to T_{max}.

For precipitation, which has an asymmetrical or gamma-like distribution, biases in high precipitation values are generally greater than biases in lower precipitation amounts. (In Fig 5.2, the log value of wet-day precipitation is plotted to better highlight the ability of simulations to reproduce the observed distribution.) Biases also tend to be positive, between 20-30% for the 99th and 99.9th quantile of the distribution, indicating that the simulations consistently over-estimate values relative to observed. For lower precipitation quantiles, biases tend to be between 5-10% relative to observed precipitation amounts, except for biases in the 1st quantile which are higher. The absolute values of these biases tend to be on the order of a tenth of an inch or less, suggesting that the spike in biases at the 1st quantile might plausibly be a symptom of the tendency of global models to simulate more “drizzle” than observed in the real world, and the inability of the downscaling approach to completely correct for that flaw. Comparing the full distribution of precipitation to temperature in Fig. 5.2 confirms that the statistical model has more difficulty in simulating precipitation than temperature, due at least in part to its much greater spatial and temporal variability as compared.

For both temperature and precipitation, and for nearly every quantile value shown in Fig. 5.3, biases associated with an individual climate model can range from zero to the maximum value. This range illustrates the third uncertainty listed above, that of the differing abilities of the global models to reproduce the features of regional climate that affect conditions at each weather station.

Biases for all quantile values averaged across all climate models are non-zero. These values illustrate the second uncertainty listed above, the ability of the downscaling approach to accurately capture the relationship between large-scale climate and local conditions.

Finally, higher biases at the tails as compared to the center of the distribution illustrate both the first and second uncertainty, the first being the limited sample of historical data available to train the downscaling model, and the second being the ability of the statistical model to capture features of the distribution towards the tails.



attached to simulated values.

This last conclusion, that biases tend to be larger at the tails of the distribution, can be shown more clearly by calculating the average bias for quantiles that are extreme (0.1, 1, 99, 99.9th quantiles) and comparing those averages to the average bias for quantiles that are closer to the center of the distribution (10, 25, 50, 75, 90th quantiles) as shown in Figure 5.4.

From Fig. 5.4, it is clear that the highest biases are in precipitation, and the lowest in maximum temperature. Also, some models tend to have higher biases than others.

Does this information help to identify any global models that might provide more accurate simulations of climate change? This comparison does not readily identify any particular model or set of models as “best” (although it does provide some basis for potentially removing one model (CNRM) that performs poorly for precipitation across the entire distribution). Rather, this provides insight into the various abilities of the models to perform better when downscaled to maximum or minimum temperature or precipitation, or to the center or tails of the distribution, and therefore what amount of confidence should be

SECTION 6: CONCLUSIONS

Climate change is expected to affect Mobile and surrounding region by increasing average, seasonal, and extreme temperatures, as well as shifting precipitation patterns between seasons and over time.

Over the past 50 years, no significant and consistent trend in annual average temperature was observed across all five weather stations. Significant cooling trends in minimum temperature in April, September, and the fall season, and increases in the number of consecutive days over 95 and 100°F per year, was observed at four out of the five weather stations.

In the future, annual average temperatures are expected to warm by approximately the same amount as warm temperature extremes, whereas cold temperature extremes are projected to warm to a slightly lesser degree. In other words, the magnitude of changes in cold temperatures, including the average temperature for winter and fall months, is expected to be slightly smaller than changes in average temperatures, while the magnitude of changes in hot temperatures, including the average temperatures of warmer summer months, may be slightly greater than the change in average temperatures. Relatively large increases are expected in the number of days per year over a given high temperature threshold (e.g., 95 or 100°F), as well as in the number of consecutive days over these thresholds.

For all temperature-related indices, there is a significant difference between the changes expected under higher as compared to lower emissions by end-of-century. For many but not all of these indices, there is also a difference by mid-century. Inter-scenario differences are most pronounced for projected changes in warm and hot temperatures, and less pronounced for changes in cold temperatures.

No historical changes were observed in average annual precipitation over the last 50 years, and little change is expected in the future. There is some indication that seasonal precipitation may increase during winter and fall, particularly over the near-term to mid-century. This is balanced by consistent projections of little change to decreases in summer precipitation. However, all seasonal changes are on the order of no more than 10% relative to climatological precipitation during the period 1980-2009.

The most consistent and significant trends observed in the historical data are increases in the exceedence thresholds for accumulated precipitation. In the future, additional slight increases are projected in the amount of rainfall occurring in 24h, 48h, and 96h, as well as in maximum 3-day precipitation accumulations. However, these changes are not

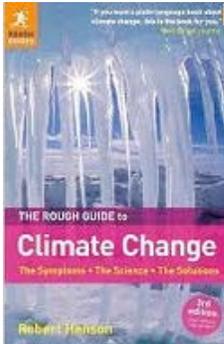
significantly different between scenarios, nor even across different time periods, suggesting that whatever mechanism may be driving these changes may not be overly sensitive to the magnitude of future global change.

There is some indication of a greater trend towards drying under higher as compared to lower emission scenarios, consistent with projected changes for the greater Southeast region. In general, however, inter-scenario differences tend to be insignificant or well within the range of uncertainty for most precipitation-related indicators.

Analysis of the bias in simulated maximum and minimum temperatures and precipitation do not reveal any particular global climate model, or sub-set of models, that consistently perform better than others in simulating observed climate over this region. Hence, using the complete multi-model mean coupled with the range continues to be the most reliable way to incorporate model or scientific uncertainty into any impact analyses.

The projections described here underline the value in preparing to adapt to the changes that cannot be avoided. Due to complex interactions between temperature and the different factors that affect precipitation in the Gulf Coast region, there is not a clear correlation between future greenhouse gas emissions and precipitation change. The effects documented in this report suggest that reducing emissions would reduce the magnitude of temperature changes, but it is not clear what would be the impact (if any) of reducing emissions on precipitation-related effects.

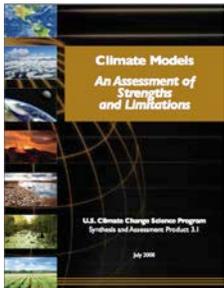
FURTHER READING



On the science and policy of climate change:

THE ROUGH GUIDE TO CLIMATE CHANGE (3RD edition)

Henson, Robert. 2011. Rough Guides, 416 pp.



On global climate models:

CLIMATE MODELS: AN ASSESSMENT OF STRENGTHS AND LIMITATIONS

A Report by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research [Bader D.C., C. Covey, W.J. Gutowski Jr., I.M. Held, K.E. Kunkel, R.L. Miller, R.T. Tokmakian and M.H. Zhang (Authors)]. Department of Energy, Office of Biological and Environmental Research, Washington, D.C., USA,

124pp.

Available online at: <http://www.climate-science.gov/Library/sap/sap3-1/final-report/>



CLIMATE PROJECTIONS FOR IMPACT ANALYSES

A PRACTICAL USER'S GUIDE

On scenario selection, global model performance, statistical and dynamical downscaling, and application and analysis of high-resolution projections to impact analyses:

CLIMATE PROJECTIONS FOR IMPACT ANALYSES: A PRACTICAL USER'S GUIDE

A report of the U.S. Fish & Wildlife Service, Dept. of Interior.

Expected Spring 2012.

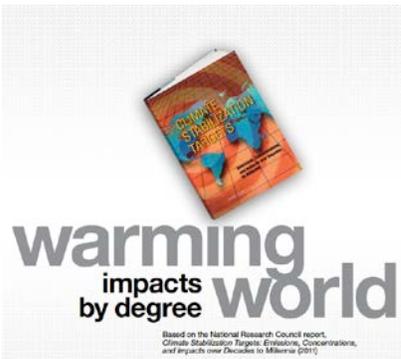


On climate change impacts by sector (water, agriculture, ecosystems, health, infrastructure, society) and for the Southeast and other regions of the U.S.:

GLOBAL CLIMATE CHANGE IMPACTS IN THE UNITED STATES

U.S. Global Climate Change Research Program, 2009. Cambridge University Press, 192 pp.

Available online at: <http://www.globalchange.gov/usimpacts/>



On synthesizing information about climate change impacts to inform decision-making and policy:

WARMING WORLD: IMPACTS BY DEGREE

National Academy of Sciences. 2011. Climate Stabilization Scenarios: Emissions, Concentrations, and Impacts over Decades to Millennia.

Available online at:

http://dels.nas.edu/resources/static-assets/materials-based-on-reports/booklets/warming_world_final.pdf

APPENDIX

Indicator Definitions

Secondary climate change indicators requested for the greater Mobile Bay region. Unless otherwise indicated, all values are calculated individually for each weather station, for 1980-2009 using both observations and historical simulations, and for the periods 2010-2039, 2040-2069 and 2070-2099 using future simulations.

1. **Timeseries** of annual average precipitation, maximum, mean, and minimum temperature from 1960 to 2099.
2. **Monthly** 30-year mean of precipitation, maximum, mean, and minimum temperature
3. **Seasonal** 30-year mean of precipitation, maximum, mean, and minimum temperature
4. **Annual** 30-year mean of precipitation, maximum, mean, and minimum temperature
5. **Seasonal and annual** 30-year average number of days and maximum number of consecutive days with maximum daily temperature $\geq 95^{\circ}\text{F}$, $>100^{\circ}\text{F}$, 105°F , 110°F
6. **Annual** 30-year mean of 4 consecutive warmest days in summer and coldest days in winter: 5th, 25th, 50th, 75th, 95th percentile
7. **Annual** coldest day and maximum 7-day average temperature with the % probability (1,5,10,50) of occurrence during 30-year period
8. **Annual** precipitation for 24-h period with a 0.2, 1, 2, 5, 10, 20, 50 % occurrence during 30-year period
9. **Annual** two and four-day exceedance probability across 2 consecutive days :0,2, 1,2, 5, 10, 20, 50 percentile and mean (note that these are calculated differently than the variable in #8 above).
10. **Seasonal** 30-year mean of largest 3-day total precipitation in each season

Dealing with Low-Frequency Quantiles

For certain variables that are sampling beyond the range of the observed historical distribution (e.g., #8 and 9), the 0.2% and 1% exceedences are identical. This is because the distributions are only based on 30 values for each period. On average, creating a distribution from only 30 points means that there will only be one value above 95% and below 5%. So anything above 95% or below 5% is not robust, as this requires extrapolating far beyond the original data used to create the distribution.

The function used here to fit quantiles uses an empirical distribution based on the data, not a theoretical distribution. More information on this routine can be found here: <http://stat.ethz.ch/R-manual/R-devel/library/stats/html/quantile.html>

However, engineers often use a Log-Pearson distribution to fit precipitation curves. This distribution is theoretical rather than empirical, which means it can extrapolate beyond the ranges of the data used to derive the distribution. For that reason, we asked: what difference would it make if a Log-Pearson fit were used to calculate the quantiles of the distribution?

For the quantiles contained *within* the range of the data, an empirical distribution is more accurate than fitting a theoretical distribution because it makes no assumptions regarding the distribution of the data. For these quantiles, differences between the two approaches would be a function of how well the theoretical distribution fit the empirical distribution.

For quantiles that lie *beyond* the range of the data (for example, the 1st or 99th quantiles in a dataset that is made up of less than 99 data points), there is a significant difference between the two approaches. An empirical approach simply assigns an out-of-range quantile the most extreme value on that side of the distribution. So, for example, if the highest value in a distribution of 20 points were 42.5 then the value of 90th quantile and any higher quantile would all be set to 42.5. This method provides a highly constrained estimate of extreme values as it does not allow estimates beyond the range of the data used to derive the distribution. A theoretical distribution, on the other hand, provides some estimate of the shape of the tail beyond the values used to make the distribution. Quantile values outside the range of the data points can then be estimated based on that distribution. Using a theoretical distribution therefore provides an extended estimate of extreme values as it permits estimates beyond the range of observed (or modeled) data.

Since the empirical approach was used to derive the quantiles in this analysis, they should be viewed as minimum estimates for these values. In reality, the values of quantiles beyond the range of the observations used to derive the distribution will be more extreme than the values given here.

Indicator Robustness

Concerns about the robustness of multiple variables were addressed by re-defining certain precipitation variables so as to sample from a greater part of the distribution. This analysis found that:

1. Any difference between the 3 scenarios is insignificant so averaging across all scenarios for precipitation extremes is recommended if the calculations sample from only 30 points.
2. General trends (or lack thereof) appear relatively robust for variable #7.

The “general drop-off” in precipitation towards the end of the century originates directly from the projections from global climate models. Maps showing projected precipitation

changes across the entire Southeast have been added to this report to place projections for the Mobile Bay area into the context of the larger geographic context. The general trends are for a decrease in summer precipitation balanced by an increase in fall and winter. Decreases become slightly stronger under higher emissions (annual average changes for A1fi: -6%, A2: -3%) compared to lower (annual average changes for B1: +2%).

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