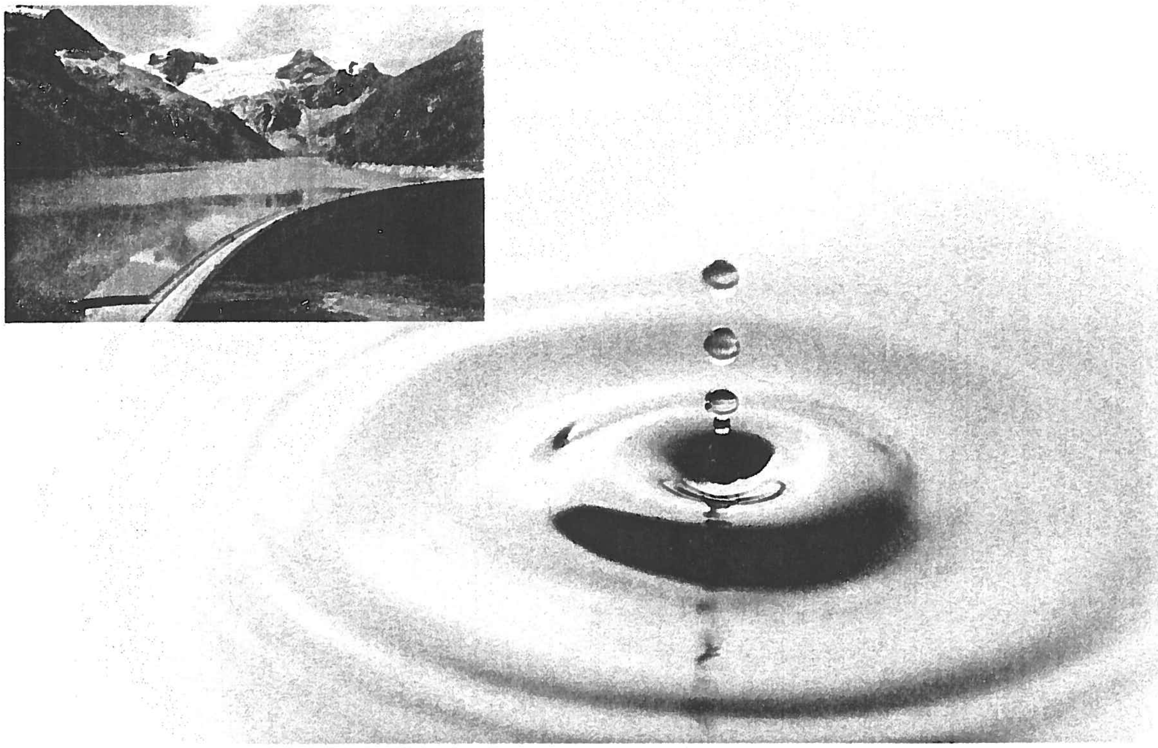

Assessment of General Circulation Models for Water-Resources Planning Applications

for
Texas Water Development Board

January 2013

Spandana Tummuri Ph.D., P.E.
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Texas Water Development Board

Final: January 30, 2013

Executive Summary

If the results from recent climate change studies are correct, climate change will impact long-term trends in temperature and precipitation in Texas. Projected temperatures will continue to increase through the 21st century. In contrast, precipitation will decrease. Finally, the incidence of extreme events is projected to increase. Extreme events (such as extended droughts, heavy rainfall, and heat waves) affect many aspects of human life. These changes will significantly impact Texas water resources.

Geographically, Texas is a large state that spans several climatic zones. Availability of water varies depending on the region of the state of interest. For example, western region climate is characterized as arid and semi-arid. As a result, the water supply is limited. In contrast, eastern region climate is generally characterized as sub-humid with abundant surface water, although the region is subject to hurricanes and flooding. Differences in projections of future conditions, which include population, supply, and demand estimates (for example), add to the uncertainty in water availability. The potential for climate change adds to the overall uncertainty of future conditions. Therefore, it important to evaluate the potential impacts of climate change and develop adaptive measures to be incorporated in the water supply planning process.

The regional and state water supply planning process in Texas is administered by the Texas Water Development Board (TWDB). The planning efforts are distributed across 16 regional planning groups. A new State Water Plan is produced over the five year duration of each planning cycle. Personnel associated with each region study water demands and water availability for both typical and drought-of-record conditions. If a water need is identified, water management strategies are proposed to address the need. The individual plans from each of the 16 regions are compiled by the TWDB into the State Water Plan.

General Circulation Models (GCMs) are complex programs developed to track the movement of the atmosphere, the distribution of water vapor, movement of energy and momentum, and interaction between the atmosphere, land processes, ocean processes, and sea ice[1]. Because GCMs model the gross processes that comprise climate, they are useful for examining the impact of *forcings* on the climate trajectory in space and time. A forcing is a component that impacts the trajectory of climate variables. Major forcings impacting the climate are natural forcings such as solar energy output, volcanic variations, and man-made forcings due to greenhouse gas variations. Models that use the natural forcings are able to closely match paleoclimate record of temperatures for the last 100 years. When greenhouse gas forcings are excluded, the models fail to simulate the warmings of the 20th century, even though the simulations of the preceding centuries using only natural forcings were successful. Therefore, one forcing of particular interest when simulating future climate is the change in greenhouse gas (GHG) concentration as a function of time and human activity. GCMs have ability to examine the impact of different greenhouse gas scenarios on projections of future

[1]Different models include different components. Some models include all of the components.

climate. Different possible projections for the future world are represented in the form of GCMs driven by different GHG emission scenarios, ranging from high concentrations (worst case emission scenario) to low concentrations (best case emission scenario). Several GCMs produced by various modeling groups are available for specific applications. A combination of GCM and the GHG emission scenario is selected from the available alternatives to obtain projected climate change data.

GCMs operate on global scale (solution domain cells with dimensions of hundreds of kilometers) and for time periods of centuries. GCM output is considered to be too coarse to be used for decision making at the major river watershed (regional) scale. The global scale output is generally processed through a regional-scale model and the output in the form of climate variables is downscaled to a regional extent. The downscaled climate variables can be input to a hydrologic model to generate variables necessary for a hydrologic analysis. The output from the hydrologic model is then considered among the regional planning tools for the region. These steps comprise a common approach for incorporating climate change uncertainty into the regional planning process.

The downscaled information currently available is not directly usable in the water availability model (WAM) used by Texas water resources engineers. An interface between the projected climate variables and WAM is required. The downscaled GCM projections should be input to a hydrologic model that can then provide the appropriate input to the WAM. The official water availability model for Texas, the Water Rights Analysis Package[2] (WRAP) was used to run a test case scenario for incorporating climate change impacted hydrologic information into the water availability estimation. Output from a GCM (CCCMA) was used to adjust input to a watershed hydrology model (Soil and Water Assessment Tool, SWAT). Net evaporation rates were also adjusted for the future climate scenario by using data from the GCM. Naturalized flows and net evaporation were obtained by running the SWAT using projected 2050 climate change scenario IS92a. Thus flow and evaporation values obtained from the watershed model, SWAT, are used to adjust WRAP inputs. WRAP was then run with the historical and projected climate change data from the SWAT tool to assess the uncertainty in the future water availability due to climate change. The results of the study indicated that water supply capabilities change significantly under 2050 climate conditions. (Wurbs and others, 2005).

Researchers and scientists in other states considered incorporation of climate change into their planning processes. The California Department of Water Resources (DWR) recently included climate change in the required standard for the Integrated Regional Water Management Planning[3] (IRWMP) process. The State of Colorado[4] is working with the Front Range Climate Change group and other climate scientists to incorporate climate change into their long-term water planning. Other states such as Washington[5], Massachusetts[6], and Pennsylvania have published guidance

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documents that advise local and regional governments on issues related to climate change.

A critical component of climate change planning in water resources is selection of an appropriate GCM (or GCMs) for downscaling the climate change data. The GCM selected for a given region should be tested for its performance and also for the need for any adjustment (during the process of downscaling), if necessary, to be used for climate change analysis. The purpose of the project described in this report is to provide TWDB personnel guidance through these issues. The specific objectives of the project are to provided assistance in the selection of one or more GCMs that are appropriate for use in State of Texas water resources planning and provide guidance on methods for downscaling GCM projections of climate change to a scale appropriate for water planning purposes.

Although more than 30 GCMs are in use by climate researchers (and others), 12 GCMs were pre-selected for the study reported herein. The pre-selection was based on model resolution and data availability for a GCM performance analysis.

Because the solution grid used in general circulation modeling is large (especially in comparison to the scale of watershed analysis), one metric for differentiating between GCMs is use of a large-scale climate feature of import to the region of interest. This approach allows assessment of GCM ability to model occurrence and trajectory of a critical climate feature. The polar jet stream that traverses the continental United States from west to east has an impact on the regional climate of Texas. Therefore, it was chosen to be the large-scale climate feature for assessing the GCM performance. The ability of each of the 12 pre-selected GCMs was tested to assess reproduction of the occurrence and trajectory of the polar jet stream over Texas geography. Of the 12 GCMs in the pre-selected group, 4 were selected based on the GCM performance analysis: GFDL CM2.1, BCCR BCM 2.0, CCSM 3.0 and CNRM-CM3. Output from these models can be used for regional downscaling purposes in Texas.

In addition to testing GCM performance, the scope of work required commentary on the range of GCM projections or convergence of selected models. The four models selected in the GCM performance analysis were tested for convergence, which confirmed that output from the selected GCMs can be used for ensemble testing. Also, an appreciation of the range of the models used for downscaling provided valuable insights into projected future trends. It was observed that projected long-term monthly estimates of average precipitation were relatively scattered, but the climate models were in general agreement with respect to the trends in long-term monthly projections of average temperature. When the future projections were compared with historic projections, climate models GFDL CM2.1, BCCR BCM 2.0, and CNRM-CM3 projected a decrease in future precipitation, while CCSM 3.0 projected an increase. Therefore, climate models GFDL CM2.1, BCCR BCM 2.0, and CNRM-CM3 converge towards similar projections of Texas climate and can be used for ensemble analysis. The projections for CCSM 3.0 model differ from those of the other GCMs. If all four models are included in an ensemble analysis, the ranges of projected weather variables will be greater than those from the three more tightly grouped models.

The process of downscaling is described in this report. In general, statistical downscaling is used for water resources planning projects. The statistical downscaling process involves comparison of GCM output over a historical period with meteorologic observations that are aggregated over an appropriately-sized grid to determine a set of transfer functions between the GCM output and regional meteorology. The transfer functions remove bias from GCM estimates of regional meteorology. These transfer functions are used with the GCM projections of future climate to developed downscaled estimates of future meteorology. The results can be used in hydrologic models to assess the potential impact of climate change on water resources. For the purposes of Texas water resources planning, the statistical downscaling approach is appropriate.

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1. Introduction

If the results from recent climate change studies are correct, climate change will impact long-term trends in temperature and precipitation in Texas. Projected temperatures will continue to increase through the 21st century. In contrast, precipitation will decrease. Finally, the incidence of extreme events is projected to increase. Extreme events such as extended droughts, heavy rainfall, and heat waves affect many aspects of human life. These changes will significantly impact Texas water resources.

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GCMs operate on global scale (solution domain cells with dimensions of hundreds of kilometers) and for time periods of centuries. GCM output is considered to be too coarse to be used for decision making at the major river watershed (regional) scale. The global-scale output is generally processed through a regional-scale model, and the output in the form of climate variables is downscaled to a regional extent. The downscaled climate variables can be input to a hydrologic model to generate variables necessary for a hydrologic analysis. The output from the hydrologic model is then considered among the regional planning tools for the region. These steps comprise a common approach for incorporating climate change uncertainty into the regional planning process.

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A critical component of climate change planning in water resources is selection of an appropriate

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[5]The Massachusetts climate change document is at `http://1.usa.gov/qQipLk` at the time of this writing.

GCM (or GCMs) for downscaling the climate change data. The GCM selected for a given region should be tested for its performance and also for the need for any adjustment (during the process of downscaling), if necessary, to be used for climate change analysis. The purpose of the project described in this report was to provide TWDB personnel guidance through these issues. The specific objectives of the project were to: [1] Provide assistance in the selection of one or more GCMs that are appropriate for use in State of Texas water resources planning and [2] provide guidance on methods for downscaling GCM projections of climate change to a scale appropriate for water planning purposes. From the request for proposals,

> There are at least 17 publicly available General Circulation Models (GCMs) available for water resources studies. The models may perform well when considered on a global scale, but when analyzed at the watershed scale may not adequately represent the observed climate in that region. Statistical downscaling is a process whereby local meteorological observations are used to improve the spatial resolution of GCM outputs. The process usually involves adjusting the GCM output such that the statistics of the modeled data match observations for the overlapping period of record. A further advantage to the statistical downscaling process is that you end up with a dataset appropriate for water resources studies on the watershed or aquifer scale.
>
> Water planners need to know which GCMs perform best in Texas. They also need an assessment of the uncertainty in the GCM climate projections for this state. The first question could be answered by determining how much each GCM needs to be adjusted in the downscaling process described above. Obviously, the ones that need the least adjustment are already performing well in this part of the world and would probably provide more reliable climate predictions. The second question can be answered by looking at the range in the projections of the GCMs for Texas — a large range indicating that there remains significant uncertainty in future climate, a narrow range meaning that the climate models are generally in agreement on a future trend.
>
> The researcher chosen should also provide a description of the downscaling techniques available and a recommendation on the appropriateness of statistically downscaled GCMs versus dynamically downscaled GCMs for hydrological studies in Texas.

A total of 12 GCMs were pre-selected based on their superior model resolutions and data availability for a GCM performance analysis. These 12 GCMs were tested for their abilities to reproduce the fluctuations of a large-scale climate feature that impacts the climate of Texas. A large-scale climate feature was chosen at a scale similar the GCMs' output in order to be a good indicator of the GCM performance. A final set of GCMs was selected based on the GCM performance analysis.

As stated in the objectives, in addition to testing GCM performance, the research team was required to provide a commentary on the range of GCM projections, or convergence, of the models selected. The models selected in the GCM performance analysis were further tested for GCM convergence. An understanding of the GCM convergence can be used to select among the GCMs for ensemble testing, in which multiple appropriate GCMs are downscaled to the same regional projections. Also, an appreciation of the ranges of the models' projections in downscaling will provide valuable insights into the future trends projected by the climate models.

In addition to the comparison of GCMs, the report also contains a comparative review of different downscaling methods. Discussion of the advantages and disadvantages of statistical downscaling and dynamic downscaling, along with some specific examples, are also included.

Pertinent background information on climate change analysis and the project are discussed in Chapter 2. Literature citations and discussion used in the development of project findings are included as appropriate. Development of downscaling technologies is discussed in Chapter 3. The details of the foundational work necessary for GCM selection are presented in Chapter 4. The methodology used to perform GCM analyses and the results obtained from those analyses are presented in Chapter 5. Finally, the conclusions and recommendations from this study are presented in Chapter 6.

1.1. Acknowledgements

We acknowledge the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP's Working Group on Coupled Modeling (WGCM) for their roles in making available the WCRP CMIP3 multi-model dataset. Support of CMIP3 dataset is provided by the Office of Science, U.S. Department of Energy. We also acknowledge the High Performance Computing Center (HPCC) at Texas Tech University, Lubbock, Texas for providing support with data storage and computing needs of the project. Finally, we acknowledge Dr. Katharine Hayhoe, Associate Professor, Texas Tech University, Lubbock, Texas for providing guidance on several queries related to the science of climate change.

2. Background and Scope

The link between carbon dioxide and climate change was first predicted by Swedish chemist Svante Arrhenius in 1896 (Arrhenius, 1896). The science of climate change has evolved since its inception and has grown to be an important research topic for the 21st century. It has been reported that several resources important for human existence are impacted by changes in the climate. Understanding the potential impact of climate change on water resources is an integral part of a sound water supply planning process. Appreciating the effects of climate change helps decision makers prioritize the mitigation/adaptation techniques to assure adequate water supplies in a time of uncertainty. This section presents a description of the mechanism of climate change and a brief summary of the processes that impact climate change. Also discussed are the details of the global and regional scales of climate change studies and their respective importance. Finally, the scope of the current study is discussed along with the proposed methodology for addressing the questions posed in the scope of work.

2.1. Science of Climate Change

Climate change is expressed as long-term shifts in the statistics of weather variables such as temperature, precipitation, relative humidity, and others. There are short-term weather extremes, distinct from the long-term fluctuations associated with climate change, that result from immediate response to climate mechanisms. Climate change is an integral part of the Earth's natural variability, which is caused by interactions among oceans, atmosphere, and land with variability in the solar radiation reaching the earth. In addition to the natural variability, certain naturally occurring gases, such as carbon dioxide (CO_2) and water vapor, trap heat in the atmosphere in a process called the greenhouse effect and can contribute to climate change. The scientific community debated the causes of climate change in last few decades. However, more recently, there has been strong consensus within the scientific community that human-induced causes are contributing to climate change. The Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) concluded, "...most of the observed increase in the globally averaged temperature since the mid-20th century is very likely due to the observed increase in anthropogenic GHG gas concentrations" (IPCC, 2007). Different mechanisms that impact climate change are described in the sections below.

2.1.1. Greenhouse Effect

The Earth's weather and climate are the result of the redistribution of heat. The energy delivered by the sun heats the earth, and the earth radiates the heat back into the atmosphere. This reflected radiation is redistributed by the ocean and the atmosphere, and the excess is radiated back into space as longer-wavelength infrared radiation. Clouds and atmospheric gases, primarily water vapor and CO_2, absorb the infrared radiation and re-emit it at much lower temperatures. This process traps part of the Earth's reflected radiation within the Earth's atmosphere, resulting in warm temperatures required for the existence of life-forms at the surface. The process by which atmospheric gases trap the re-radiated energy is similar to the effect of the glass roof on a greenhouse. Therefore, this process is called the greenhouse effect, and the gases are called GHGs. The average annual surface temperature of the Earth is approximately 60°F. This temperature is maintained because of GHGs. The greenhouse effect is essential for the existence of human life. The only disadvantage is that the greenhouse effect works adversely if the concentrations of the GHGs are higher or lower than the optimal levels[1]. According to the National Academy of Sciences (2008), the increase in the concentrations of the GHGs, due to both natural and anthropogenic sources, caused a 1°F increase in the Earth's surface annual mean temperature in the past century, and surface temperatures in the past two decades have risen at a rate substantially greater than 1°F per century (3–4°F). Hence, an appropriate representation of the complex physical processes that contribute to change in climate must include the impact of GHG emissions.

2.2. IPCC

The Intergovernmental Panel on Climate Change[2] (IPCC) is an international scientific body that was jointly established in 1988 by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP). The primary goals of the IPCC are:

1. To assess scientific information related to climate change,
2. To evaluate the environmental and socio-economic consequences of climate change, and
3. To formulate realistic response strategies.

Since its establishment, the researchers associated with the IPCC produced a series of Assessment Reports (Houghton et al., 1990; Houghton, 1995; IPCC, 2001, 2007) that included a compilation of climate projections developed by independent climate modeling groups. The IPCC is the principal scientific unit curating and developing projections of climate change and its impacts on different sectors of human life, thereby providing access to climate change information produced by different research groups. The IPCC reports played a major role in assisting governments to adopt and implement policies in response to climate change. The reports are standard references, widely used by policymakers, scientists, and researchers.

[1] National Academy of Science, `http://www.nasonline.org`, 2008.
[2] The main web page for the IPCC is located at `http://www.ipcc.ch/` at the time of this writing.

2.3. Greenhouse Emission Scenarios

Based on the CO_2 projections described in IPCC SRES report, on an average, CO_2 levels are generally assumed to peak at 475 ppm by the middle of this century and stabilize at 400 ppm by the end of the century (IPCC, 2007). There is not one precise number because the sensitivity of the climate system to the greenhouse gases is quantified differently for each emission scenario and cannot be estimated exactly. (IPCC, 2007). Because GHGs have an impact on the temperature levels, a maximum permissible CO_2 level of 400 ppm is generally required to maintain temperature level increases less than 2°F. The basic premise of climate modeling is that the physical and chemical processes that affect climate can be adequately described by GCMs. GCMs provide a means to quantitatively capture and represent the effects that GHGs have in influencing climate. Therefore, quantification of the increases in GHG emissions is necessary for sound climate change projections. However, uncertainty in quantifying future GHG emissions is based on variations in future population growth, economic growth, and technological changes.

Projected future increases in CO_2 levels are expressed relative to 1990 standard levels (IPCC, 2007). For the last four decades, climate modelers used climate models to compare projections for two scenarios, a present represented by current CO_2 levels ($1\times CO_2$) and a future scenario represented in terms of multiples of CO_2 rates for the present scenario ($2\times CO_2$). The limited processing power of computers and incomplete understanding of climate dynamics necessitated this coarse representation. In 1992, IPCC released emission scenarios to drive global circulation models and to develop climate change scenarios. They developed six scenarios designated IS92 a-f for the Business-As-Usual (BAU) case. BAU meant that the GHG emissions were represented by existing trends without any adjustments. The IS92 a-f scenarios were the first set of global emission scenarios to provide estimates for all GHGs (such as CO_2, SO_2, water vapor, CH_4; IPCC, 2007).

In 1996, IPCC representatives conducted a plenary session in Mexico City to develop a new set of emission scenarios. The report describing the methodology and the formulation of these new scenarios is the Special Report on Emission Scenarios (SRES, Nakicenovic and Swart, 2000). The new set of emissions scenarios was intended for future IPCC assessments and for other scientific and policymaking communities that develop mitigation/adaptation measures and policies. The new scenarios also contain information to better assess climate-change impacts and vulnerabilities, adaptation strategies, and policies. They represent the level of economic activity, rates of technological advancements, and demographic developments in different world regions.

The A1 emission scenario depicts a future world of low population growth, rapid economic growth, and rapid introduction of new and more efficient technologies. The scenarios represent a global population that peaks in the mid-21st century. This scenario projects a more interactive society with social and cultural convergence among regions and substantial reduction in per capita income gap between the developed and the developing countries. The A1 scenario is further divided into three groups based on the direction of the technological change:

- A1F1 represents fossil-fuel-intensive energy consumption,
- A1T represents use of non-fossil energy resources, and

- A1B represents a balance of energy sources.

The A2 emission scenario was developed to represent a heterogeneous world. This storyline projects more self-reliance, preservation of local identities, and high population growth. In this scenario, economic development is primarily regionally oriented. Per-capita economic growth and technological changes are more fragmented and slower than in other emission scenarios.

The B1 emission scenario was developed under the assumption of a convergent world with low population growth and an environmentally friendly future. Similar to the population growth in the A1 scenario, the global population was assumed to peak near the mid-21st century and declines thereafter. In this scenario, there is a rapid change in economic structure with a shift to a service- and information-based economy, reduction in material intensity, and introduction of robust, resource-efficient technologies. Importance is given to global solutions for economic, social, and environmental sustainability. The scenario concentrates on improved equity without additional climate initiatives.

The B2 emission scenario was developed to describe a world in which local solutions are provided to economic, social, and environmental sustainability. In it, a world with moderate population growth, moderate levels of economic development, and diversified technological change is depicted, which is in contrast to the B1 and A1 scenarios. The focus is on the regional and local levels.

GHG emissions over time associated with the emission scenarios described above are displayed on Figure 2.1. Additional information on the emission scenarios is contained in the IPCC 4th Assessment Report (Rogner et al., 2007).

2.4. Why Should We Study Climate Change?

According to the National Academy of Sciences[3], increases in GHG concentrations caused a 1°F increase in the surface mean temperature during the past century. Surface temperatures in the past two decades, 1991 to 2010, rose at a rate substantially greater than the 20th century average rate. With the increase in GHG concentrations, scientists predict that the mean global surface temperature could increase by 2-10°F during the 21st century. Simultaneously, northern hemisphere snow cover and Arctic Ocean floating ice decreases. Sea level increased 4–8 inches during the past century. Furthermore, world-wide precipitation increased about one percent with a significant increase in extreme rainfall events. The 10 warmest years of the 20th century occurred during the last 15 years of the century. Other impacts observed during the last century were melting of the Greenland ice caps between 1992–2002, loss of glaciers in Austria, rise in sea level in the Maldives region and islands around it, and stress in the South American coral population attributed to climate-change-induced El Niño events.

Although climate change is a global phenomenon, the impacts of such changes are more apparent at regional and local scales. Impacts could be in the form of higher or lower temperatures, longer or shorter growing seasons, and higher or lower frequency of droughts and hurricanes (IPCC, 2001).

[3] See `http://www.nasonline.org`, 2010.

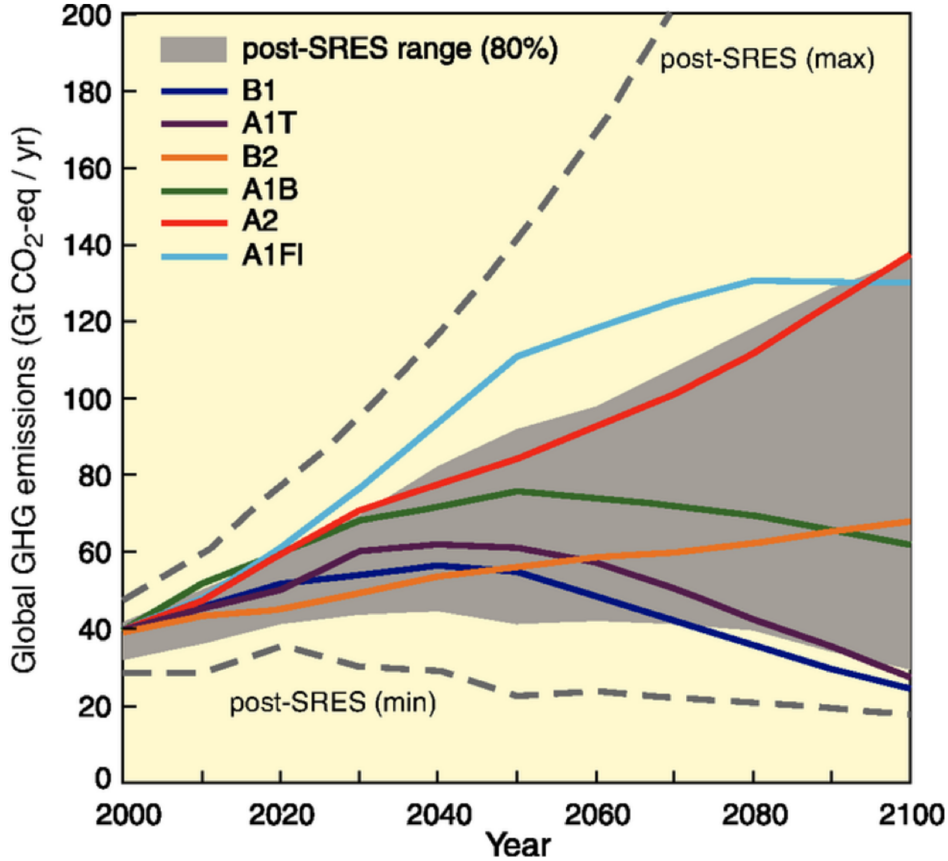

Figure 2.1: SRES emission scenarios. (Source: IPCC, 2007, Figure 3.1)

It is important for impact modelers to analyze changes in the regional environment caused by global climate change and propose policies to accommodate those changes. With respect to water resources, scientists project decreasing precipitation and soil moisture and increases in temperature and evaporation (IPCC, 2001). Such impacts affect different portions of the hydrologic budget for a specific region. Global warming and its effects on a region's water resources are important and much-studied subjects.

Climate modeling and impact studies are important to the State of Texas because of its large size. Texas is larger than most states and spans climates from arid/semi-arid regions in the west, to a sub-humid climate in the east, to the hot, humid coastal regions along the Gulf Coast. The Texas Gulf Coast is at greater risk from sea-level rise compared to other North American coastal areas because of relatively flat topography and land subsidence (Norwine et al., 1995). Semi-arid conditions and high potential evapotranspiration rates in western Texas might impose stress on the state's water resources should climate change result in warmer, drier conditions. Because of the size and the variety of Texas climate mechanisms, policy makers need assessment of the potential impact of climate change for policy development, especially when considering new construction projects.

2.5. How Do We Study Climate Change?

GCMs are used to study climate change at a global scale. These models are complex, deal with numerous intricate climate mechanisms, and require astronomically-large numbers of calculations to produce results. GCMs provide a broad perspective of the climate change occurring at continental scales. GCMs do not generate results at regional scales because the grid size used in GCMs is large (2–8° latitude by 3–10° longitude). GCMs tend to simplify most of the sub-grid scale phenomena (those processes occurring for areas comparable to regional scale) to maintain consistency in model structure (IPCC, 2001). These complex models produce global long-term projections for climate variables, such as precipitation, temperature, and sea-level atmospheric pressure, at monthly and daily time steps for periods encompassing several centuries into the past and the future.

2.6. Importance of Regionalization

The spatial scale (size of the solution grid) of a GCM is relatively coarse. Therefore, GCM output is not appropriate for regional or smaller scales. For many impact studies, resolution of climate change requires information at a regional scale, which is substantially finer (smaller) than the large scales represented by GCMs. For example, an entire watershed for a sizable river can be contained in one grid cell of a GCM. Therefore, methods for regionalizing or downscaling GCM results are needed.

To formulate policies to regulate the emission of GHGs, it is important that the long-term effects of the increase in the GHG concentrations are adequately represented in the models used to aid in policy development. It is important to account for GHG emissions as represented by the SRES while regionalizing the GCM information. As a result, several approaches for downscaling GCM data to a regional scale were developed. The sections below contain a brief description of different quantitative and qualitative approaches for downscaling the GCM results. Detailed discussion of these downscaled techniques in summarized in Chapter 3.

2.6.1. Statistical Downscaling

In statistical downscaling, a statistical model that relates large-scale climate variables (or predictors) to regional and local variables (or predictands) is developed, and the local and regional variables are estimated. Local and regional climate statistical parameters are estimated using the predictors from a GCM output as input parameters for the statistical model. The advantage of statistical downscaling techniques is that they are computationally inexpensive. Statistical downscaling methods can easily be applied to output from different GCM experiments. Another advantage of the statistical methods is the possibility of tailoring the model to observed regional or local weather data (IPCC, 2001).

The basic assumption prevalent in the downscaling methods is that the statistical relations developed for current climate conditions will hold under the changed future forcing conditions, and this assumption unfortunately is not verifiable. There is no universal systematic procedure for checking the uncertainty of the statistical models. Therefore, verification of statistical models should be carried out on a case-by-case basis based on the historical data available (IPCC, 2001).

2.6.2. Dynamic Downscaling

Another technique of regionalization is dynamical downscaling or generation of a regional climate model (RCM). The procedure used for developing a RCM is similar to that used for a GCM except that the grid size is small compared to that of a GCM. The advent of fast computers resulted in easier implementation of RCMs for climate modeling. RCMs with comparatively small solution domains (when compared with GCMs) can yield significant modification of large-scale circulations, often leading to improved simulations. Improper representation of physical relations in the form of incorrect assumptions is a problematic issue with GCMs. These errors caused by parameterization could be eliminated to a large extent using the RCM. The boundary conditions and initial input values for a regional climate model are obtained from a GCM, and the internal physical consistency of the model is maintained (IPCC, 2001).

2.6.3. Qualitative Approach

For those regions with limited technical resources and data availability issues, a preliminary assessment of the impact of climate change on the sectors can be developed using a relative change or qualitative approach. The California DWR [4] summarizes the relative change approach as addition or subtraction of a defined quantity or percentage from the expected level of a variable of interest to estimate the impact of climate change. The approach produces a preliminary estimation of the expected magnitude and direction of expected change. Another qualitative approach relies on impact assessment from past studies and surveys of local experts. This approach can be used to indicate the general direction and order of magnitude of the expected changes due to climate change, developed based on qualitative information.

2.7. Defining the Climate of Texas

The climate of Texas is controlled by the radiation balance and the flow of weather into Texas from the neighboring regions. The continental and regional-scale of interest examined herein were:

- Pacific tropical storms (jet stream),
- Atmospheric moisture from the Gulf of Mexico in the east, and
- Other large-scale climate features such as the proximity to Chihuahuan Desert, Pacific/North American teleconnection pattern (PNA) and the Pacific Decadal Oscillation (PDO).

[4] See `http://www.water.ca.gov.`, 2010.

2.7.1. Pacific Tropical Storms

El Niño is a disruption in the ocean atmosphere system that causes important weather systems around the globe (Philander, 1990)[5]. Under normal conditions, relatively high atmospheric pressure on the eastern Pacific Ocean compared to the western Pacific Ocean results in the trade winds blowing towards the west across the tropical Pacific Ocean. These winds result in the build-up of warmer surface water in the west. Upwelling replaces the warm surface water caused by the winds with cold water from the depths of ocean. The trade winds push the water further towards the west causing an increase in the altitude of water in the western Pacific compared to the eastern region. The surface waters in the west undergo evaporation that rises and then condenses to form clouds. These clouds result in wet weather in the western Pacific. While the air rises in the west, the moist air from the east rushes in to fill in the empty space left by the warm air, causing rain in the west. This cycle strengthens the trade winds, and the process begins again. During some point of this cycle, the air pressure gradient declines because of the Southern Oscillation. The southeast trade winds weaken and allow the warmer surface water that was moving westward to drift eastward along the equator and then southward towards the Peruvian coast. This abnormal scenario is called the El Niño. El Niño occurs with a frequency of three to five years. During an intense period of El Niño, the southeast trade winds shift direction and change into equatorial westerlies. This phenomenon is known as El Niño Southern Oscillation (ENSO). La Niña means just the opposite of El Niño. La Niña refers to a stage with exceptionally strong winds and low sea surface temperatures in the central and eastern tropical Pacific. The effect of El Niño events and climatic variations in the equatorial Pacific region is extremely strong and is well documented in the literature. The effect of El Niño events on other regions on the globe is an example of teleconnection, when weather anomalies at one region could be related to climatic variations at a remote location.

Extreme events such as hurricanes and droughts are a part of the natural climatic variability of Texas. These variabilities exist even in absence of global climate change. The external influences such as the ENSO cycle in the Pacific Ocean also have an impact on the drought/flood cycle of Texas. A La Niña event results in a decrease in the precipitation levels of the region. The impact of these events on Texas can be emphasized by the fact that a drought (1988) in Houston (when rainfall was half of its annual average) coincided with an occurrence of La Niña. In more recent memory, the widespread drought of 2011 was also associated with a La Niña event.

2.7.2. Gulf of Mexico

Another large-scale climate feature impacting seasonal climate of Texas is the moist air blowing inland from the Gulf of Mexico. The proximity to the coast primarily influences the seasonal climate of Texas. The Gulf acts as a moisture source for the region and modulates the seasonal and daily cycles. The atmospheric systems that define the seasonal and diurnal variations in temperature and precipitation vary by their seasonal positions in Texas. Sea surface temperatures and surface winds associated with the Gulf of Mexico moderate temperature extremes. During the spring

[5] Also, information about the Souther Oscillation is available from `http://www.noaa.gov`.

and fall seasons, the influence is attributable to passage of the frontal systems generally moving from the west to the east. The fronts are positioned in the northeasterly direction. The moist air is carried northward from the Gulf with the advancing front wedging under warmer moist air. This movement results in frontal precipitation that may lead to severe weather. In winter, the fluctuations are mostly caused by the cold, dry, Canadian air blowing from the north.

2.7.3. Other Large-Scale Climate Features

The proximity of Texas to the Chihuahuan Desert results in periods of prolonged below-average rainfall. The Chihuahuan Desert air mass contracts and expands with respect to the migration and strength of the large-scale subtropical ridge of high pressure that envelopes the earth around the equatorial region. The strength and existence of the ridge depends on the occurrence of El Niño and volcanic eruption. Texas experiences drought with intermittent frequency. The High Plains is the most vulnerable region because of proximity to the Chihuahuan Desert. Especially during the winter, the intrusions of dry polar air are frequent, and the return flow of the moist Gulf air above the shallow polar air mass does not extend far enough into the region to produce appreciable rainfall. The regions affected by the drought are determined by the location of the subtropical ridge over the southern United States.

Other teleconnection patterns such as the PNA and the PDO exist in this region, but no strong link to climate in Texas has been observed. After a thorough literature review, we confirmed that the other large-scale climate features did not have a pronounced impact on the climate of Texas.

2.8. Scope of the Study

The purpose of this study is to provide guidance to water resource planners on the issues listed below.

1. The GCM models may perform well when considered on a global scale, but when analyzed at the watershed scale may not adequately represent the observed climate in that region. Hence, there is a need to downscale the information produced by GCMs. However, because the downscaling or regionalization process is heavily reliant on the GCM information, it is necessary to select the most appropriate GCMs for the regional scale studies. Therefore, water planners need to know which GCMs perform best for different regions in Texas. Also necessary is assessment of the uncertainty in the GCM climate projections for this state.

2. As outlined in Section 2.6, there are several methods in which GCM information can be downscaled to a regional scale. One of the goals of this study is to present a qualitative description of various downscaling techniques and provide a recommendation on the appropriateness of statistically downscaled GCMs versus dynamically downscaled GCMs for hydrologic studies in Texas.

2.9. Approach for the Study

While there are several GCMs available, the primary goal of this study was to select appropriate climate models that best represent the global-scale climate of Texas. GCMs that efficiently represent the climate forcings of regions in Texas were selected based on a careful comparison of the output from 25 GCMs for selected GHG emission scenarios. The selection was based on a two-step process testing the GCM performance and GCM convergence. Details of the GCM testing process are discussed in Chapter 5. In testing the GCM performance, the abilities of the GCMs to reproduce the trends of a continental- scale climate feature were compared, and the GCMs that performed better were pre-selected. The large-scale climate feature that most impacts the regional climate of Texas was found to be the polar jet stream. Testing the ability of GCMs to properly represent the latitudinal location of the center of the polar jet stream for any given historical month helped in the pre-selection of the GCMs. The test of GCM performance determined how much each GCM required to be adjusted to match with the real-time features in the downscaling process. Obviously, the ones that needed the least adjustment were already performing well in this part of the world and would probably provide more reliable climate predictions.

The pre-selected GCMs were further analyzed for GCM convergence. A GCM output usually includes future projections of mean climate variables, such as precipitation, temperature, and relative humidity. The convergence of all models can be used to determine the range in the projections of the GCMs for Texas. The convergence test is focused on determining whether all models were converging towards a similar result or varied over a large range of values— a large range indicating that there remains significant uncertainty in future climate projections, a narrow range meaning that the climate models are generally in agreement on a future trend. Therefore, the projection capabilities of GCMs for these climate variables were compared, to test the convergence of different climate models and those models that converged better were identified.

Finally, a qualitative comparison of the literature available on different downscaling techniques was developed to address the second goal of the study. Details of the downscaling techniques are presented in Chapter 3.

3. Downscaling Techniques

Downscaling is the process of extracting information about projected climate change from GCM output and rescaling that information from the large computational cells of the GCM to smaller scales such that the results can be used for regional and watershed studies. The majority of literature review work was directed toward understanding current technology associated with the downscaling GCM. That information is the topic of this chapter of the report.

3.1. Dynamic Downscaling

Dynamic downscaling generally refers to using a regional climate model embedded within (or at least using results from) a larger-scale GCM. Regional climate models are numerical models constructed to reproduce meteorologic/climatologic variables at scales from a few tens of kilometers to a few thousands of kilometers (Wilby et al., 2004). They are more detailed in their representation of the physical processes associated with climate and generally offer improved representation of climate physics. Therefore, because of their complexity and the computational expense of operating them, they can be applied to solution domains with lateral dimensions of only a few hundred kilometers.

Although regional climate models have other applications, from a downscaling perspective they are useful because some of them can be embedded within one ore more computational cells of a GCM. That is, the computations executed in the course of operating a GCM can be used as the boundary and initial conditions for a more detailed regional climate model. The potential impact of climate forcings can be studied using the results from the regional climate model that is "nested" within the solution domain of the much coarser (larger) solution domain of the GCM (Giorgi et al., 1998). Mearns et al. (2003) offers a review and suggestions for application of regional climate modeling for downscaling.

3.2. Statistical Downscaling

Statistical downscaling is used to describe the process of extracting information from GCM output for a "historical" GCM run, comparing those results to observationally-derived data, and then using a climate-change run of the GCM to "adjust" the variables of interest for subsequent projections. Because GCM output is developed on a grossly different scale than observational measurements, bridging that gap is often done by rescaling observational data on a grid and working with the gridded observational data. The process is described by several authors and is elaborated in the following section of this report.

One of the earliest projects to address the potential impacts of climate change was that of Ayers and Leavesley (1989) and Ayers et al. (1994). A GCM was used to predict potential changes to precipitation and temperature based on the changes from a base run ($1\times CO_2$) and a climate-change run ($2\times CO_2$). The main approach used a "climate-factor" adjustment for downscaling.

Bogardi et al. (1993) described development of a stochastic spatiotemporal model developed to estimate the impact of climate change on local and regional precipitation for eastern Nebraska in the United States. Epstein and Ramirez (1993) developed a spatial disaggregation model for the upper Rio Grande basin in Colorado. The model preserved spatial covariance structures for the temperature and precipitation regimes, and allowed simulation of daily temperature and precipitation using direction provided by the GCM output. Bates et al. (1998) described a hidden Markov model for application to the downscaling problem in southwest Australia.

Widmann et al. (2003) compared three methods for statistical downscaling of GCM output. Their database was 522 stations from which daily data were projected onto a 50 km$\times$50 km grid. The grid-cell estimates were developed to be consistent with the Parameter-Elevation Regressions on Independent Slopes (PRISM) precipitation climatologies developed by Daly et al. (1994). Widmann et al. developed and applied 1) a spatially-varying, but temporally-invariant scaling factor, 2) singular value decomposition of local and reanalyzed precipitation, and 3) a nonlocal dynamic correction to the local scaling factor to their dataset. The first method captured about 30 percent of the variance of observed monthly precipitation. The second method explained more than 60 percent of the variance. Finally, the local scaling method performed well, but with less skill than the second method in the rain shadow of the Cascade Mountains.

Salathé (2005) suggested a relatively simple method for statistical downscaling. They subdivided the year into quarters (December-January-February, etc.) for their downscaling approach. For precipitation, they applied a multiplicative factor to precipitation based on correlation between monthly observed precipitation and monthly reanalysis results from the GCM of interest. Monthly temperature for the grid was assumed to be the average of daily maximum and minimum surface temperatures. A correction factor was determined by computing the additive difference between grid temperature and results from the GCM reanalysis output. Daily variability of surface temperature was preserved using an observed sequence of daily temperatures constrained to the monthly mean, which is similar to the approach used by Wood et al. (2002).

Hayhoe et al. (2008) described climate change predictions for the Northeastern U.S. developed using statistical downscaling and regional climate modeling (dynamic downscaling). Hayhoe et al. used the method of Wood et al. (2002). In the Wood et al. method, the density functions for modeled monthly precipitation and temperature for the calibration period were mapped onto gridded historical data (from observations) to preserve the mean and variance of the underlying observational time series. Daily humidity values were developed using the method described by Thornton et al. (2000).

Hayhoe et al. (2009) described climate change predictions for the U.S. Midwest derived by statistically downscaling GCM output. The process was described as using a historic period of observed variables of interest to establish relations between ground-observed variables and GCM-predicted variables. The relation was averaged over at least two decades to reduce year-over-year variation. A second historical period was used to validate the derived relations. The assumption was that relations between large-scale GCM processes and small-scale local processes remains constant under climate-change scenarios. Vrac and Naveau (2006) reported that for 37 midwestern states the relations broke down only for the most extreme precipitation events — those exceeding the 99th percentile of the frequency distribution[1]. Furthermore, Hayhoe et al. (2008) reported that statistical methods might outperform regional climate models for geographic areas of variable topography, such as mountainous or coastal areas. As a result, Hayhoe et al. (2009) chose to use two statistical downscaling schemes. The first approach was similar to that developed by Maurer et al. (2002). That is, an empirical statistical approach was used that maps the density functions for modeled monthly and daily precipitation and temperature for the climatologic period (1961–1990) onto the 1/8 degree gridded observed data. This approach preserved the mean and variance of the observations. Furthermore, bias correction and disaggregation were developed using the methods of Wood et al. (2002), which compared favorably with regional climate model simulations. The second approach used by Hayhoe et al. (2009) was an asynchronous regression approach to rescale daily GCM temperature output by individual quantile. GCM-simulated time series were conditioned such that the distributions of simulated daily values approximate distributions of temperature at local weather stations. The regression equations so derived were used with future GCM simulations to rescale GCM simulations under climate-change conditions.

Hayhoe et al. (2010) described the statistical downscaling approach used for climate change assessment in the Great Lakes region of the U.S. They stated the following.

> Statistical downscaling relies on historical instrumental data for calibration at the local scale. A statistical relationship is first established between GCM output for a past "training period," and observed climate variables of interest (here, daily maximum and minimum temperature and precipitation). This relationship is averaged over a climatological period of two decades or more to remove year-to-year fluctuations. The historical relationship between AOGCM output and monthly or daily climate variables at the regional scale is then tested using a second historical "evaluation period" to confirm the relationship is robust. Finally, the historical relationship between AOGCM output and monthly or daily climate variables at the regional scale is used to downscale both historical and future AOGCM simulations to that same regional scale.

The primary assumption for the Hayhoe et al. (2010) statistical downscaling approach was that the relations between large- and small-scale processes were invariant with respect to time, which was a weakness of the approach. Hayhoe et al. (2010) used two statistical downscaling approaches. The first was an empirical technique that mapped the probability density functions for modeled monthly and daily precipitation and temperature for the climatological period (1961–1990; Maurer et al., 2002) onto those of gridded historical observed data, so the mean and variability of both monthly

[1]However, it should be noted that for many hydrologic analyses these are the values of interest.

and daily observations are reproduced by the climate model outputs. The bias correction and spatial disaggregation technique was originally developed for adjusting AOGCM output for long-range stream flow forecasting (Wood et al., 2002; VanRheenen et al., 2004), later adapted for use in studies examining the hydrologic impacts of climate change. The method compared favorably to regional climate model simulations (Wood et al., 2004). The second approach downscaled to individual weather stations using an asynchronous quantile regression method that can determine relationships between two quantities not measured simultaneously, such as an observed and a model-simulated time series. The method assumed that, although the two time series were independent, they described the same variable, at approximately the same location, and therefore must have similar probability density functions (PDFs). The two independent time- varying variables $X(t)$ and $Y(t)$ were regressed using only their statistical distributions $F(x)$ and $G(y)$. The method determined the function $Y = u(X)$ by matching the quantiles of x and y of the distributions of X and Y for each probability level (O'Brien et al., 2001). Using 2 m daily model-simulated maximum and minimum air temperature and precipitation from the AOGCM as the predictor and daily observed maximum and minimum temperatures and precipitation as the predict and, the resulting regression model could then force the PDFs of the simulated fields to match those of the observed data.

Wang et al. (2011) discussed results from a comparison of statistical downscaling and dynamic downscaling as applied in California to assess potential impacts of climate change for water resources projects. The Wang et al. (2011) comparison appeared to be based on an unpublished manuscript or white paper[2] in which the PRISM system for developing relatively high resolution gridded datasets was used to produce downscaled results from GCMs.

3.3. Weather Generators

A weather generator is a stochastic model developed using known or assumed probability distributions to describe weather variables that are connected in space and time to preserve spatial and serial correlation. Therefore, weather generators are a form of statistical downscaling, but are generally used to produce suites of potential time series. They are complicated tools that require substantial investment to develop and operate. Weather generators are used with GCM output by making adjustments to some of the parameters that describe the variables of interest. The process is to develop the statistics of meteorologic variables of interest from the climate model operated under historical conditions, then develop similar statistics from climate model outputs when operated under climate-change conditions. The differences in statistics are used to adjust commensurate statistics derived from observed meteorology. The weather generator is then used to sample the distributions (preserving the spatiotemporal dependence) stochastically to produce suites of meteorologic instances for driving hydrologic models.

Dubrovsky (1997) developed a weather generator based on a Markov-modeling approach. A climate-pattern analysis was also used.

[2]Cited as Wang, Yin, Suits, and Chung (Wang et al.) and provided by Wang as a personal communication (August 2011).

Semenov and Barrow (1997) described application of a weather generator (stochastic model) for development of climate change scenarios[3]. Semenov and Barrow used the UKHI and UKTR GCM experiments from the UK Meteorological Office GCM to develop suites of simulated weather for assessment of potential climate change impacts on agriculture. They concluded that use of 30 years of simulation from the downscaled GCM experiments produced very different assessments of the sustainability of wheat cultivation in the area near Seville, Spain.

Semenov et al. (1998) conducted a comparison of the WGEN (Richardson and Wright, 1984) and LARS-WG stochastic weather generators at 18 sites located in the USA, Europe, and Asia. They reported that the LARS-WG weather generator tended to match observed data better than WGEN because the distributions used in LARS-WG were more complex (semi-empirical) than those used in WGEN (simple theoretical). Neither weather generator was able to reproduce the annual variability in monthly means of climate variables. In addition, the distributions of frost and hot periods were not reproduced. Furthermore, the daily variance of climate variables was also not reproduced. Semenov et al. observed that validation of the models is critical to establishing confidence in the model output and for obtaining good results.

Khalili et al. (2007) described a weather generator approach based on a spatial moving average to describe inter-site correlation. They applied the method to the Peribonca River basin in Quebec. Such a model would be used by adjusting the parameters of the stochastic model to correspond with the expected changes from a GCM. Khalili et al. (2009) extended the work of Khalili et al. (2007) to include other meteorologic variables, including daily maximum/minimum temperatures and solar radiation data. The WGEN (Richardson and Wright, 1984) weather generator was used without modification. Meteorologic variables were reproduced using spatially-correlated random variables. The resulting meteorologic time series preserved the spatial correlation structure for both daily and monthly time steps.

3.4. Hydrologic Applications

Hughes et al. (1987) presented an analysis of the use of GCM output for prediction of impacts on hydrologic extremes using a weather pattern classification approach that was coupled to a stochastic model (weather generator). An example of output from their approach is displayed on Figure 3.1.

An early study on the detectability of a climate-change signal on the runoff from a river based was examined by Hains and Henry (1989). The examined runoff from the Chattahoochee River basin in northeastern Georgia. They concluded that (at that time) hydrologic models lacked the structure to interact directly with output from GCMs and the necessary capability to use gridded data (such as NEXRAD precipitation fields).

Chang et al. (1992) presented a review of research on climate change impacts on water resources. They identified three research needs to be addressed by climate change research:

[3]The stochastic weather generator, LARS-WG (Semenov and Barrow, 2002), was available at `http://www.rothamsted.bbsrc.ac.uk/mas-models/larswg.php` at the time of this writing.

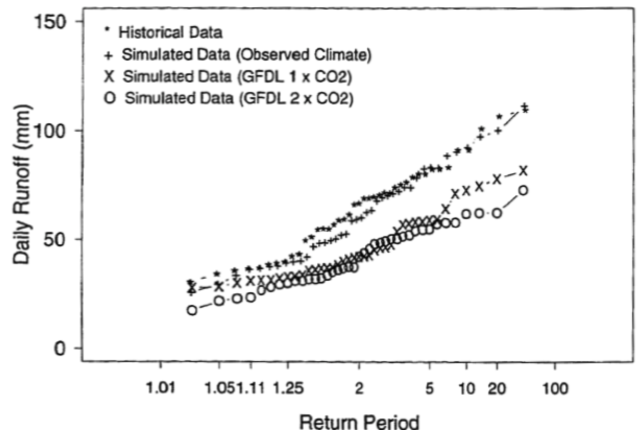

Figure 3.1: Daily flood-flow frequency curve for the Satsop River from Hughes and others (1987).

1. Need for water managers to clearly describe hydrologic statistics and characteristics needed from climate change researchers for application in developing estimates of climate change on water resources systems,
2. Need to estimate impacts of climate change on water resources systems, and
3. Need to evaluate water management and planning methods to determine if uncertainty in fundamental assumptions (primarily stationarity) implies revisions to these technologies are required.

At the time of the Chang et al. (1992) review, no detailed lists of climatic and hydrologic data requirements were identified. Little work was revealed dealing with the sensitivity of water resource systems nor were extensive sensitivity analyses of climate change scenarios determined.

Chiew et al. (1995) used a daily time-step hydrologic model to examine the impact of projected climate change on runoff and soil moisture for 28 Australian catchments. Chiew et al. applied an arbitrary set of changes to temperature and precipitation to effect a sensitivity analysis. They followed this set of experiments with results from five different GCMs[4] (CSIRO9, BMRC, UMOH, GFDLH, and CCC models). The approach of Chiew et al. (1995) appears to be an application of the climate factor downscaling approach. They used a combination of arbitrary changes to temperature and precipitation in a pseudo-change or sensitivity analysis approach, then followed that with adjustments based on temperature and precipitation differences predicted by the suite of GCMs used in their study. The absolute results are unimportant to the TWDB research project; however, the approach is important as it illustrates an application of the climate factor method.

Chiew et al. (1996) examined application of catchment-scale rainfall-runoff models for use with GCMs. They concluded that the simple parameterization models could be directly used in GCMs for relatively wet (subtropical) watersheds, but did not work well for watersheds with ephemeral flows.

[4]Forcing scenarios in use at the time of the Chiew et al. paper were limited to $1\times CO_2$ and $2\times CO_2$.

Copeland et al. (1996) used the Colorado State University Regional Atmospheric Modeling System to examine the impact of natural versus current vegetation on the weather and climate for July 1989. This study demonstrated an interesting alternative approach to the typical application of numerical models for climate-change assessments. Copeland et al. reported that these changes resulted in substantial changes in both the positive and negative directions on temperature, humidity, wind speed, and precipitation — solely from changes in vegetation cover.

Wood et al. (2002) conducted a long-term study of hydrologic forecasting for a portion of the eastern United States. They used monthly ensemble climate model forecasts from the GSM[5] code. The GSM model output was bias-corrected and downscaled to $1/8°$ horizontal resolution and disaggregated for a daily time step. The bias-correction step was effected using GSM model climatology as a sample, determining the empirical frequency distribution of model outputs, then using derived percentiles from model output to determine quantiles based on observed frequency distributions of model outputs. The Wood et al. development of bias-correction on gridded GCM output and meteorologic data is the approach used by many (if not most) researchers and end-users of GCM output to downscale. Wood et al. (2002) used the Variable Infiltration Capacity model (VIC, Liang et al., 1994) to represent the hydrology of interest, as they explained in the following quotation.

> The premise of the bias correction step is that despite biases in GSM-simulated climate, the GSM forecasts may have a useful signal if interpreted relative to the GSM climatology rather than the observed climatology. The GSM climatology is defined by the monthly distributions (for months 1–6 in the forecast period, separately) of simulated GSM P_{tot} and T_{avg} taken from the GSM hindcast simulations (i.e., the 210 simulated values for each of the 6 forecast period months, for each variable). The monthly observed climatology spans the same time period as the GSM output (1979–1999) and was created from Co-op station daily observations averaged to a monthly timestep and to the GSM grid resolution; hence the observed monthly distributions for P_{tot} and T_{avg} are defined by only 21 values per variable. Bias correction is achieved by replacing GSM forecast values for T_{avg} and P_{tot} with values having the same percentiles (nonexceedence probabilities) with respect to the observed climatology that the original GSM values had with respect to the GSM climatology, for a given month. The forecasts are subsequently expressed as anomalies (temperature shift and precipitation percentage) with respect to the observed monthly means for the 21-year climatology period. Bias correction is performed at the GSM scale, and each GSM cell (23 cells spanned the study region) is treated individually, defining its own set of monthly distributions.
>
> For example, bias correcting a monthly T_{avg} forecast for January–June requires the following steps: (1) The January GSM T_{avg} is assigned a nonexceedence probability (or percentile) within the 210-value GSM climatology distribution for January T_{avg}. (2) A January T_{avg} having the same nonexceedence probability in the observed climatology is then calculated. (3) Steps 1 and 2 are repeated for T_{avg} in months February–June, and the entire process is repeated for each of the ensemble forecast members. (4) Finally,

[5]National Centers for Environmental Protection/Climate Prediction Center Global Spectral Model.

the bias-corrected forecasts are expressed as additive (for T_{avg}) and multiplicative (for P_{tot}) anomalies.

In the precipitation and temperature bias correction scheme, when either the GSM output or the associated percentile falls above or below the range of empirical Weibull percentiles (equal to $\frac{1}{(N+1)}$ and $\frac{N}{N+1}$, where N is the number of members from which the probability distribution is estimated), theoretical probability distributions are fit to the data to extend the empirical distributions. This becomes necessary because the historical climatology is defined by the 21 years of historical observations, whereas the model ensembles consist of a larger 210-member dataset. For low precipitation, an Extreme Value Type III (Weibull) function was used, with a minimum lower bound of zero; whereas for extreme high precipitation an Extreme Value Type I (Gumbel) distribution was employed. For temperature, a normal distribution was used for both minimum and maximum.

Following bias correction, the monthly GSM scale forecast anomalies are translated to the spatial and temporal scale of Variable Infiltration Capacity (VIC) model inputs. The T_{avg} and P_{tot} anomalies are spatially interpolated to the 1/8° VIC cell centers and applied to the monthly observed 1979–1999 1/8° cell means, to create monthly forecast sequences at the VIC model scale, in the following manner:

$$\begin{aligned} T_{\text{VICfcst}}(m,e) &= T_{\text{VICmean}}(m) + T_{\text{ANOMfcst}}(m,e) \\ P_{\text{VICfcst}}(m,e) &= P_{\text{VICmean}}(m) + P_{\text{ANOMfcst}}(m,e) \end{aligned}$$

Here $T_{\text{VICfcst}}(m,e)$ is the forecast monthly T_{avg} for a given VIC cell in month m ($m = 1 \ldots 6$) of a forecast ensemble member e ($e = 1 \ldots 20$). $T_{\text{VICmean}}(m)$ is the observed 1979–1999 mean T_{avg} for month m, and $T_{\text{ANOMfcst}}(m,e)$ is the additive T_{avg} forecast anomaly for month m and ensemble member e. Likewise, $P_{\text{VICfcst}}(m,e)$ is the forecast monthly P_{tot} for a given VIC cell in month m of a forecast ensemble member e, $P_{\text{VICmean}}(m)$ is the observed 1979–1999 mean P_{tot} for month m, and $P_{\text{ANOMfcst}}(m,e)$ is the multiplicative P_{tot} forecast anomaly for month m and ensemble member e. The addition of temperature anomalies will hereafter be referred to as shifting, and the multiplication by precipitation anomalies will be referred to as scaling.

The final step in preparing the forecasts for input to the VIC model is to replace the monthly mean sequences by daily sequences. For each month (e.g., January) in each forecast ensemble, one year from the climatology period is randomly selected (e.g., 1988). For each VIC cell, the observed daily values of precipitation for the selected year and month (e.g., 1988, January) are scaled so that the monthly total precipitation is equal to the forecast P_{tot} for the ensemble member and month. The resulting values of daily precipitation become the daily sequence for that month of the particular forecast ensemble member. Daily T_{min} and T_{max} from the same selected year (e.g., 1988) are shifted equally so that their average, $(T_{\text{min}} + T_{\text{max}})/2$, reproduces the monthly forecast T_{avg} for the ensemble member and month, and the resulting values of T_{min}

> and $T_{\max}$ become the daily sequence for that month of the particular forecast ensemble member. Daily wind speed is taken without adjustment from the VIC daily values for the selected year and month, forming the fourth daily forcing used by the VIC model. The same year is used to select the daily data for a given month of an ensemble forecast member in every cell of a study area (the Ohio River basin and east coast). Using the same year-month combination for resampling over the large-scale hydrologic units helps to preserve a degree of spatial synchronization in the weather components driving hydrologic response. The random sampling of a climatology year for selection of daily sequences is repeated for each month in each forecast ensemble member.
>
> We performed a test of this method using observed total monthly precipitation and average temperature time series for 1979–1999, aggregated to the GSM scale, as raw forcings over the Ohio River drainage area. These large- scale forcings were processed (using the interpolation and temporal disaggregation steps) into daily VIC scale forcings, with which we simulated streamflow. Figure 3.2 shows that the method is able to reproduce the mean and variance of the basin streamflow climatology without introducing substantial method-related bias.

Andréasson et al. (2004) used two GCMs and two RCMs to study the impact of proposed climate-change scenarios on six watersheds in Sweden. Andréasson et al. used what they termed the *delta change* approach. The delta change approach determines changes in relevant climate variables between the control and scenario climate simulations and these changes are applied to the hydrologic simulations. Andréasson et al. observed considerable range in the results of the hydrologic impacts produced during their study. They attributed these differences to a number of components, including: geographical location of test basins, emissions scenarios, GCMs, RCMs, time periods used for base climate determination, and how the hydrologic models were connected to the RCM results. Their principal observations were: decreased spring flood peaks, decreased summer runoff in southern Sweden, predominantly decreased annual runoff in southeastern Sweden, decreased frequency of high flow events during spring, increased autumn and winter runoff, increased annual runoff volumes in northern Sweden, and increased frequency of high flow events in autumn.

Adam and Lettenmaier (2007) used the VIC model (Liang et al., 1994; Nijssen et al., 1997, VIC,) to simulate spatially-distributed total runoff (quick- and slow-response runoff) and snowmelt over global land areas using a 0.5° resolution for an historical and a future time period. Climate-change forcing was achieved by adjusting historical, observation-based precipitation and temperature based on average-change factors from 15 GCMs.

Cunderlik and Simonovic (2007) examined the potential impact of climate change on flood risk using an inverse approach. A hydrologic model was used to transform hydrologic risk and vulnerability to corresponding meteorologic conditions. The frequency of critical meteorologic conditions was examined using a weather generator, which was linked to the GCM of interest. The application was for Ontario, Canada.

Kang and Ramirez (2007) coupled downscaled output from a GCM with a deterministic hydrologic model to assess the response of streamflow to long-term rainfall variability under a climate-changed

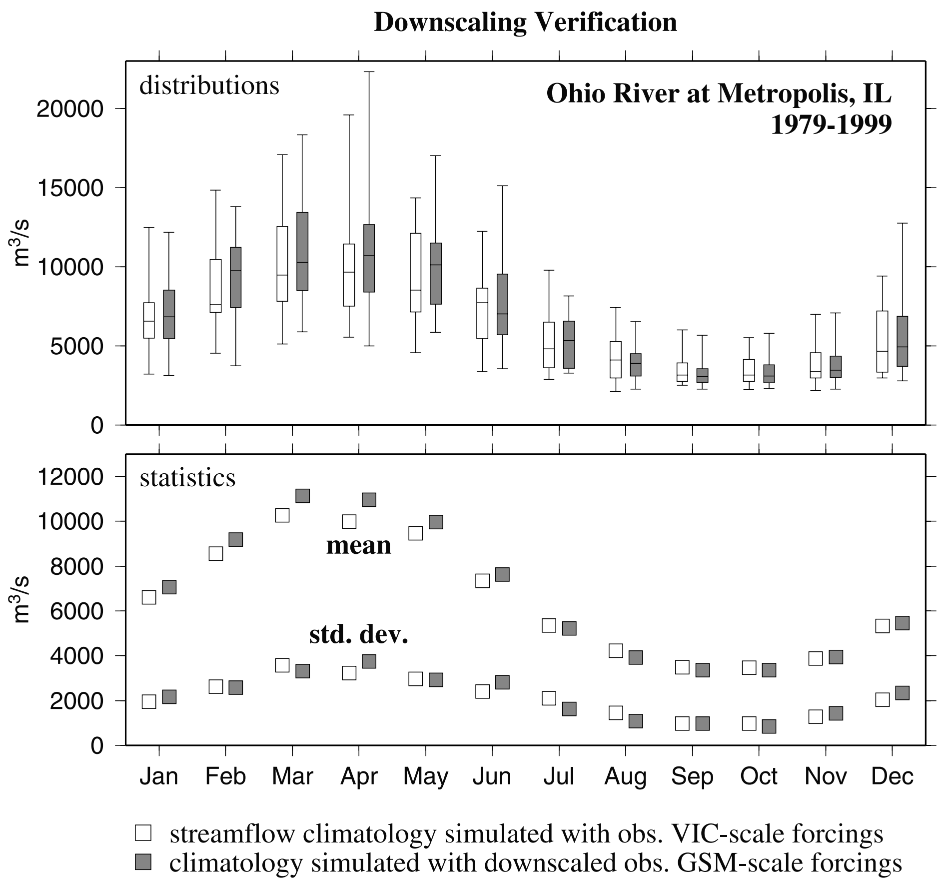

Figure 3.2: Climatology period (1979–1999) streamflow distribution simulated from daily VIC 1/8° observations compared with parallel simulation from monthly GSM-scale (2.8125°) spatially-averaged observations after downscaling and disaggregation procedure. (This figure is Figure 5 reproduced from Wood et al. (2002).)

scenario. They used the CGCM2[6] and the IPCC B2 scenario to determine the changed climate. Downscaling was effected using a spatiotemporal stochastic random cascade model (weather generator) to account for spatial intermittency and spatial self-similarity. The tools were applied to the South Platte River basin. Results from the study were that the distribution of peak flowrate is more sensitive to spatial variability than total runoff volume, that impact on total runoff and peak flowrate can exceed greatly the magnitude of the rainfall variation, and that the magnitude of the impact depends strongly on the magnitude of associated changes in evapotranspiration.

Abdulla and Al-Omari (2008) examined the long-term hydrologic response of a semi-arid watershed to potential climate change. The climate change scenarios superimposed on the Zarqa River (Jordan) were derived from a combination of General Circulation Models (GCMs) and assumed

[6]Canadian Centre for Climate Modeling Version 2.

changes in climate. The Hadley and MPI GCMs were used for two scenarios. An additional ten scenarios were constructed by assuming +2C and +4C temperature rise and assuming 0%, +10%, +20%, -10%, and -20% changes in precipitation. The Surface-Infiltration-Baseflow model of the watershed system was used to examine potential changes in watershed response. Under the climate change scenarios studied, monthly watershed runoff decreased.

CH2M Hill (2008) conducted a climate-change impact study to determine potential impacts on the LCRA-SAWS Water Project. They analyzed results from 112 GCM simulations of the Lower Colorado River basin, settling on eight climate-change scenarios based on results from two GCMs. The two GCMs were the GFDL-CM2.1 and CCSM3, developed by personnel at the Geophysical Fluid Dynamics Laboratory (USDC, NOAA) and National Center for Atmospheric Research, respectively. The climate-change scenarios were the A2 (moderately high) and B1 (moderately low) emission scenarios. Downscaling results were obtained from the Lawrence Livermore National Laboratory Coupled Model Intercomparison Project (Phase 3).

Choi (2008) applied the A2 and B2 IPCC scenarios to the Kishwaukee River basin coupled with a dynamic urban growth model[7] to obtain a suite of eight combined climate-land-use scenarios. Output from the HadCM3 GCM was used. Choi concluded that impacts were primarily related to surface runoff, which was a relatively small portion of total runoff. Impacts were observed in the summer and low-flow seasons and implied that water-sensitive crops might be seriously impacted.

Adam et al. (2009) examined potential changes to snowmelt hydrology based the approach developed for regional studies in the western United States. Projected changes to snowpack and the timing of snowmelt-derived runoff were greatest near the boundaries of areas that currently experience substantial snowfall. Such changes reflected, at least quantitatively, the character of observed changes in the western United States.

3.5. Available Downscaled Datasets

A large group of governmental and research agencies pooled resources to produce a set of statistically-downscaled climate projects. These agencies include the U.S. Department of the Interior's Bureau of Reclamation (Research and Development Office), Lawrence Livermore National Laboratory, Bureau of Reclamation's Technical Service Center, Santa Clara University Civil Engineering Department, Climate Central, Scripps Institution of Oceanography, and U.S. Geological Survey. The effort was supported by the U.S. Department of Energy's National Energy Technology Laboratory, the U.S. Army Corps of Engineers Institute for Water Resources, the U.S. Geological Survey's Climate and Land Use Science Applications and Decision Support Program and National Research Program, and Scripps Institution of Oceanography's NOAA-funded California-Nevada Applications Program (a Regional Integrated Science and Assessment project) and California Energy Commission-funded California Climate Change Center. The collected datasets are housed in one publicly-available archive[8].

[7] Land use Evaluation and impact Assessment (LEAM) model.

[8] The website is located at `http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/dcpInterface.html` at the time of this writing.

Downscaling of GCM output was conducted using the method developed by Wood et al. (2004). Bias[9] was removed from the GCM output before downscaling. The downscaling process was then executed to produce each dataset. Statistical downscaling requires three datasets: 1) gridded data based on ground station observations (generally for the 20$^{\text{th}}$ century) with a spatial resolution of 1/8°, 2) GCM output for a historical period (generally comprising at least a portion of the gridded observation-based dataset), and 3) GCM output for the future period. The basic protocol for developing the daily downscaled datasets (BCSD) is as follows.

1. Bias Correction
   (a) For each variable in the GCM dataset to be analyzed, aggregate the observed gridded data from 1/8° to a spatial resolution of 2°.
   (b) Extract a pair of observational and GCM historical period datasets with the same period of record (both at the 2° resolution).
   (c) For each month (January–December) and for each grid cell, construct cumulative distribution functions of GCM- and observational-based variables.
   (d) Rank the GCM and observational values from greatest to least (or vice versa — sorting is irrelevant) and compute the empirical probability ($P = \frac{n}{(N+1)}$).
   (e) **Critical Concept** — For the future period, determine an adjusted probability using the same value from the historical period GCM output. Select the observed value for that probability. Then assign the future period probability to the observed value.
   (f) The result is the bias-corrected estimate for the future period. When combined with bias-corrected GCM output for the historical period, the result is a dataset that is statistically consistent with the gridded observed dataset for the historical period, but retains the GCM-predicted changes to statistical parameters from the historical to the future periods.
2. Spatial Downscaling
   (a) Determine a spatial climatology pattern to be used to disaggregate the bias-corrected GCM output. The spatial scale of the bias-corrected GCM output will be 2° (if the algorithm presented above is followed) and the objective is to disaggregate to 1/8°. The mean monthly spatial pattern (for each month) for each variable could be used.
   (b) A *factor value* is computed for each cell and for each month in the simulation period. For precipitation, it is the ratio of the bias-corrected GCM depth to the observational value and for temperature it is the difference between the bias-corrected GCM temperature and the observational temperature.
   (c) Apply a spatial interpolation function to map the computed factors from the 2° cells onto the 1/8° cells. The approach used as an example on the archive collaborators[10] website is the SYMAP algorithm by Shepherd (1984).

[9] Bias in this context refers to the difference between historical-period GCM output and historical-period gridded meteorological observations.

[10] The archive collaborators are the Climate Central (CC) Lawrence Livermore National Laboratory (LLNL), Bureau

(d) Apply the factor for each 1/8° cell to the precipitation or temperature to compute the bias-corrected, spatially-downscaled value for each cell and each time step.

Results from application of this algorithm for a large number of GCMs and a wide range of emission scenarios are presented by the archive collaborators on a publicly-available website[11]. The downscaled datasets are available for monthly (BCSD) and daily (BCSA) time steps. Temporal resolution finer than one day will probably require custom development of the downscaled dataset and depends on the resolution of the underlying GCM.

3.6. Jet Latitude Index Analysis

Bradbury et al. (2002) conducted a study on the New England (NE) region to understand the primary climate mechanisms controlling the intra-seasonal and multi-annual winter season climate change in New England. Although these researchers concluded that significant teleconnections existed between the NE climate and the North American Oscillation (NAO) and PNA indices, the mechanism behind these links is unclear because of the proximity of NE to the centers of actions for NAO and PNA. In an attempt to characterize the NE regional atmospheric low so as to better understand the dominant mechanisms driving the winter climate clearly, Bradbury et al. (2002) developed the Jet Latitude index (JLI). JLI is an important index used to relate upper air patterns and regional climate. The JLI was developed by Bradbury et al. (2002a) to understand the seasonal variation of the latitudinal location of the polar front. Improved modeling of northeastern winter climate variability resulted from use of correlation between JLI indices and upper air patterns. The principles used to generate the JLI indices and their gridded data could be applied to analyze similar synoptic scale climates in other regions of the United States. Bradbury et al. (2002a) stated that although few regional climate studies adopted such techniques, additional studies focused on this geographical region would result in better understanding of the relationship between upper air climate patterns and regional surface climate variability. The authors also stated that the simple and generic format of these indices make them useful for efficiently analyzing the ability of GCMs to represent the upper air climate patterns.

JLI was developed initially for the NE region. JLI represents the monthly mean position of the polar front jet based on 200 mb zonal winds. The location of the polar front is determined from the latitude of maximum zonal winds in the 20°N to 60°N range. The JLI is equal to the average latitude of maximum zonal winds in between longitudes ranging from 65°W to 80°W. JLI was not assigned to all the months because the singular regional jet was not clearly identifiable in the index domain for some months. The isolation of the months with more than one apparent jet was carried out by rejecting data points for the months where the maximum zonal wind velocity observed at any longitude (from 65°W to 80°W) was identified at the vertical domain boundary. For any given

of Reclamation, Santa Clara University (SCU), Scripps Institution of Oceanography (SIO), U.S. Army Corps of Engineers (USACE), and U.S. Geological Survey (USGS). The website is `http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/dcpInterface.html` at the time of this writing.

[11] The website was `http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/dcpInterface.html` at the time of this writing.

month, the index value was not assigned if the observed maximum zonal wind velocity at one longitude was greater than 12° north or south from the maximum zonal wind velocity observed at any other longitude. These automated screening procedures were proven to be effective at removing most months lacking a clearly distinct jet or having more than one predominant jet within the index domain. Months with unclear or indistinct jets or months with more than one jet within the index domain were eliminated efficiently using automated screening procedures.

A JLI similar to the one generated for the NE was developed by Bradbury and others (2002) for the study sites in Texas. The comparison study was carried out for 12 GCMs and their datasets and the realtime observations. GCM data were input into the JLI model developed by Bradbury and others (2002), and the output was analyzed to determine the jet stream representation of each GCM.

4. Foundational Work for GCM Selection

A number of tasks were required to gather the background information necessary for the GCM selection analysis. The details of different tasks and their relevance to the GCM selection process are described in this chapter. The foundational details necessary for GCM selection included the details of the study area(s), the details of the GCMs used in the study, the meteorological information used for calibrating the model, and the GHG emission scenario used for the study. Additional comments on foundational work necessary for GCM selection are provided in subsequent sections of this chapter.

4.1. Selection of Study Areas

The purpose of this section is to describe the process of selecting the study areas to represent different geographic regions in Texas and to present the details of the chosen study areas. The work associated with this task addressed the following questions.

1. What are the different factors that influence the selection process for the study areas for this project?

2. Where should the study areas be located so that they optimally represent variability across the state of Texas?

There are several factors that can impact the selection of study areas for this project. Most of the factors are specific to the region and the study purpose. Listed below are the factors that impacted selection of the different geographic regions and subsequent study areas.

1. Regions with different precipitation zones (high/low rainfall)
2. Regions with different evaporation zones (arid/semi-arid/humid)
3. Regions with different population zones (urban/rural)
4. Regions with water-rights permitting issues
5. Regions with different topography
6. Regions with good availability of meteorological data

TWDB staff and the project team discussed and initially agreed on four study areas to represent State of Texas climate regimes. These four study areas were selected such that they were distinct from one another in terms of the factors listed above and represented the four extreme geographical regions of Texas (north, south, east, and west). After preliminary analyses of the available meteorological records for the state, the project team learned that five regions were necessary to characterize the major variability across the state. Because the GCM selection process dealt with GCM output that was generated for model grid cells at latitudinal/longitudinal scales, the boundaries of the study areas were defined by latitude/longitude combinations instead of county lines or watershed boundaries and river basins. The study areas used for this project are depicted on Figure 4.1. The nomenclature used in the study to refer to the study areas is listed in Table 4.1.

Table 4.1: Details of the study areas used for GCM selection analysis.

Study Area	Geographical Region	Latitude (°N)	Longitude (°W)
1	East	28–31	93–100
2	South	24–28	97–100
3	Northwest	32–37	100–104
4	Northeast	31–34	93–100
5	Far West	29–32	100–107

4.2. Selection of GCMs

After selecting the study areas, the next task was to collect information from the GCMs to be considered. Research groups operating coupled ocean-atmosphere GCM simulations are required to archive model output by the Program for Climate Model Diagnosis and Intercomparison (PCMDI). There are 25 climate modeling groups. Output from their GCM simulations were included in the PCMDI dataset and the World Climate Research Programme's (WCRPs) Coupled Model Intercomparison Project Phase 3 (CMIP3) multi-model dataset. Output from these models are available for distribution to working groups and researchers worldwide. GCM output used in this study were simulated as part of the preparation of the IPCC fourth assessment report. A fifth assessment report is currently underway, but the results of GCM simulations for the fifth assessment report were not available in time to be used for this project. Pertinent details for GCMs considered for this study are listed in Table 4.2. Of these 25 models, the first 12 (Numbers 1–12) were selected for further review on the basis of relative ease and extent of data availability in combination with appropriate model resolution. The remainder (Numbers 13–25) were eliminated from further consideration.

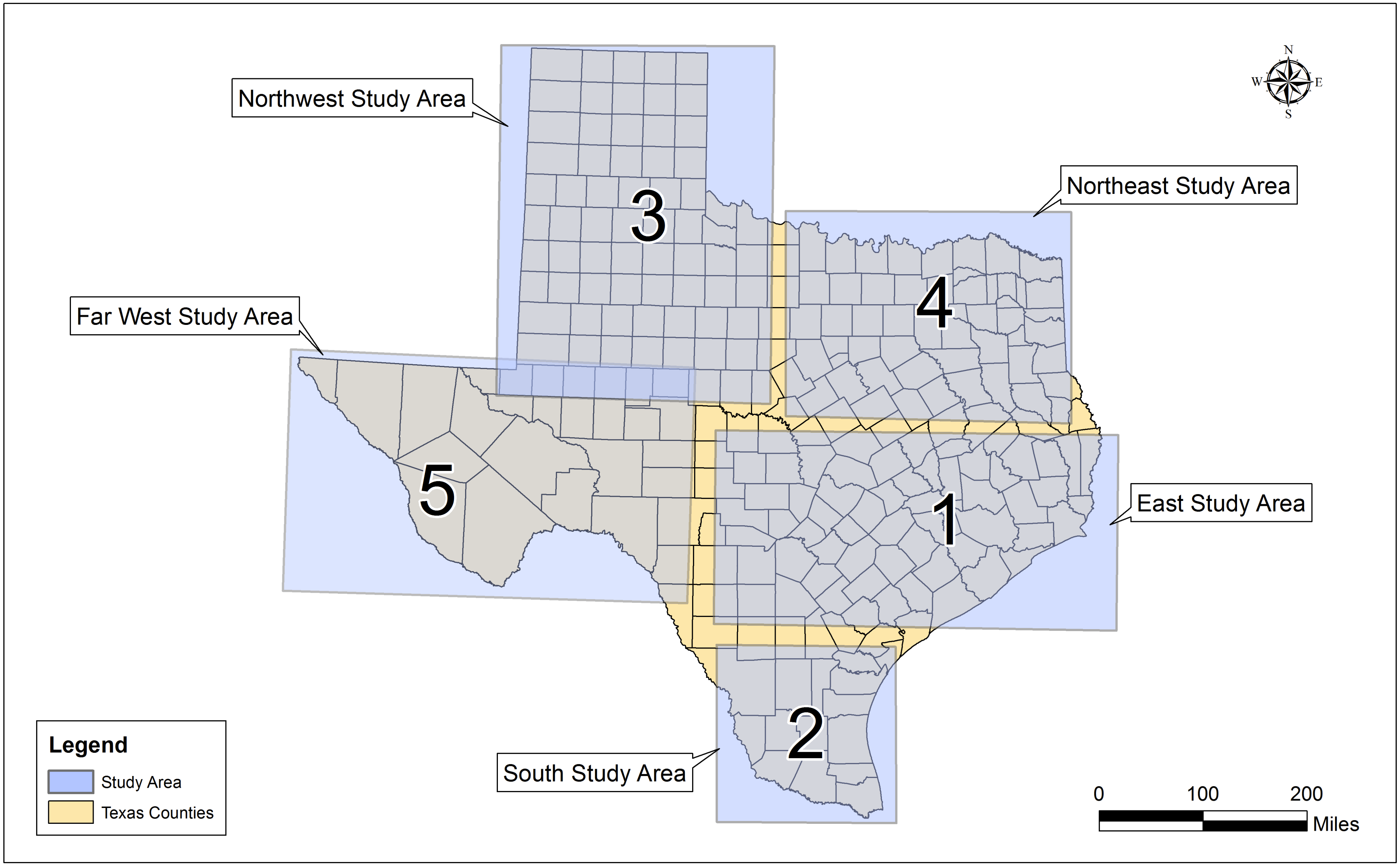

Figure 4.1: Study areas used for GCM selection analysis.

Table 4.2: Climate Models used for GCM Selection Analysis.

No.	Originating Group(s)	Country	CMIP3 I.D.	Model Name	Lat/Long	Spectral Resolution
1	Hadley Centre for Climate Prediction and Research/Met Office	UK	UKMO-HadGEM1	Hadley Global Environmental Model V1	1.25×1.875	
2	National Center for Atmospheric Research	USA	CCSM3	Community Climate System Model V3	1.4×1.4	T85
3	CSIRO Atmospheric Research	Australia	CSIRO-Mk3.0		1.875×1.875	T63
4	Max Planck Institute for Meteorology	Germany	ECHAM5/MPI-OM	Max Planck institute of Meteorology	1.875×1.875	T63
5	US Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory	USA	GFDL-CM2.1	Geophysical Fluid Dynamics Laboratory—Climate Model	2.0×2.5	
6	Institut Pierre Simon Laplace	France	IPSL-CM4	Institut Pierre Simon Laplace Climate Model	2.5×3.75	
7	Hadley Centre for Climate Prediction and Research/Met Office	UK	UKMO-HadCM3	Hadley Centre for Climate Prediction Research Climate Model	2.75×3.75	
8	Meteorological Research Institute	Japan	MRI-CGCM2.3.2	Meteorological Research Institute, Japan Climate Model	2.8×2.8	T42
9	National Center for Atmospheric Research	USA	PCM	Parallel Climate Model	2.8×2.8	T42
10	Bjerknes Centre for Climate Research	Norway	BCCR-BCM2.0	Bergen Climate Model V2	2.8×2.8	T42
11	Canadian Centre for Climate Modelling & Analysis	Canada	CCCMA-CGCM3.1(T63)	Coupled Global Climate Model - Third Generation	2.8×2.8	T63
12	Météo-France/Centre National de Recherches Météorologiques	France	CNRM-CM3	Climate Model V3	2.8×2.8	T42
13	Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC)	Japan	MIROC3.2(hires)	Model for Interdisciplinary Research on Climate	1.125×1.125	T106
14	Beijing Climate Center	China	BCC-CM1	Climate Model V1	1.875×1.875	T63

Continued on next page

Table 4.2: Climate Models used for GCM Selection Analysis. — Continued.

No.	Originating Group(s)	Country	CMIP3 I.D.	Model Name	Lat/Long	Spectral Resolution
15	US Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory	USA	GFDL-CM2.0	Geophysical Fluid Dynamics Laboratory Climate Model	2.0×2.5	
16	LASG/Institute of Atmospheric Physics	China	FGOALS-g1.0		2.8×2.8	T42
17	Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC)	Japan	MIROC3.2(medres)	Model for Interdisciplinary Research on Climate	2.8×2.8	T42
18	NASA/Goddard Institute for Space Studies	USA	GISS-AOM	Goddard Institute for Space Studies—Atmosphere Ocean Model	3.0×4.0	
19	Canadian Centre for Climate Modelling & Analysis	Canada	CGCM3.1(T47)	Coupled Global Climate Model—Third Generation	3.75×3.75	T47
20	Institute for Numerical Mathematics	Russia	INM-CM3.0	Institute for Numerical Mathematics Climate Model	4×5	
21	NASA/Goddard Institute for Space Studies	USA	GISS-EH	Goddard Institute for Space Studies—Atmosphere Ocean Model E20 with HYCOM Ocean Model	4.0×5.0	
22	NASA/Goddard Institute for Space Studies	USA	GISS-ER	Goddard Institute for Space Studies—Atmosphere Ocean Model E20 with Russell Ocean Model	4.0×5.0	
23	CSIRO Atmospheric Research	Australia	CSIRO-Mk3.5	CSIRO Mark 3.5 GCM		
24	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA, and Model and Data group.	Germany / Korea	ECHO-G			T30
25	Instituto Nazionale di Geofisica e Vulcanologia	Italy	INGV-SXG		1.125×1.125	T106

4.3. Selection of Climate Change Uncertainty Scenarios

Section 2.3 contains detailed descriptions of the different climate change uncertainty scenarios available for climate change analysis. TWDB personnel directed the project team to use the SRES A1B GHG emission scenario for the GCM selection analysis. The A1B scenario is a moderate emission scenario when compared to the other scenarios. The A1B scenario represents a future with rapid economic growth and rapid transition to more efficient technologies. The scenario represents a global population that peaks in mid-century. The A1B scenario includes a technological change that is achieved by a balance of energy sources. The A1B scenario was selected because it provides a balanced (mid-high/mid-low) representation of a future impacted by climate change.

4.4. Meteorologic Data Used for GCM Selection Analysis

Meteorologic records for precipitation and temperature variables were used for comparison and calibration purposes. Records were obtained from the National Climatic Data Center (NCDC) archives[1]. A thorough analysis of the geographic and temporal extents of data records was performed to determine a list of meteorologic stations in Texas counties with relatively long records (exceeding 30 years). Those counties containing stations with relatively long meteorologic records are presented on Figure 4.2. The counties from Figure 4.1 were further sorted based on the project study area containing them and are listed in Table 4.3. Meteorologic data for counties listed in Table 4.3 were used in the GCM selection process.

Table 4.3: Texas counties used for collecting meteorological observations for different study areas.

		Study Area		
1	2	3	4	5
Bexar	Bee	Childress	Angelina	Culberson
Brazos	Cameron	Dallam	Dallas	El Paso
Comal	Hildago	Lubbock	Erath	Midland
Galveston	Jim Wells	Potter	Greg	Tom Green
Guadalupe	Kleberg	Taylor	McLennan	Val Verde
Harris	La Salle		Palo Pinto	Winkler
Jefferson	Nueces		Rusk	
Kimble			Smith	
Matagorda			Tarrant	
Medina			Wichita	
Travis				
Victoria				

[1]The NCDC archives are available at `http://www.ncdc.noaa.gov` at the time of this writing.

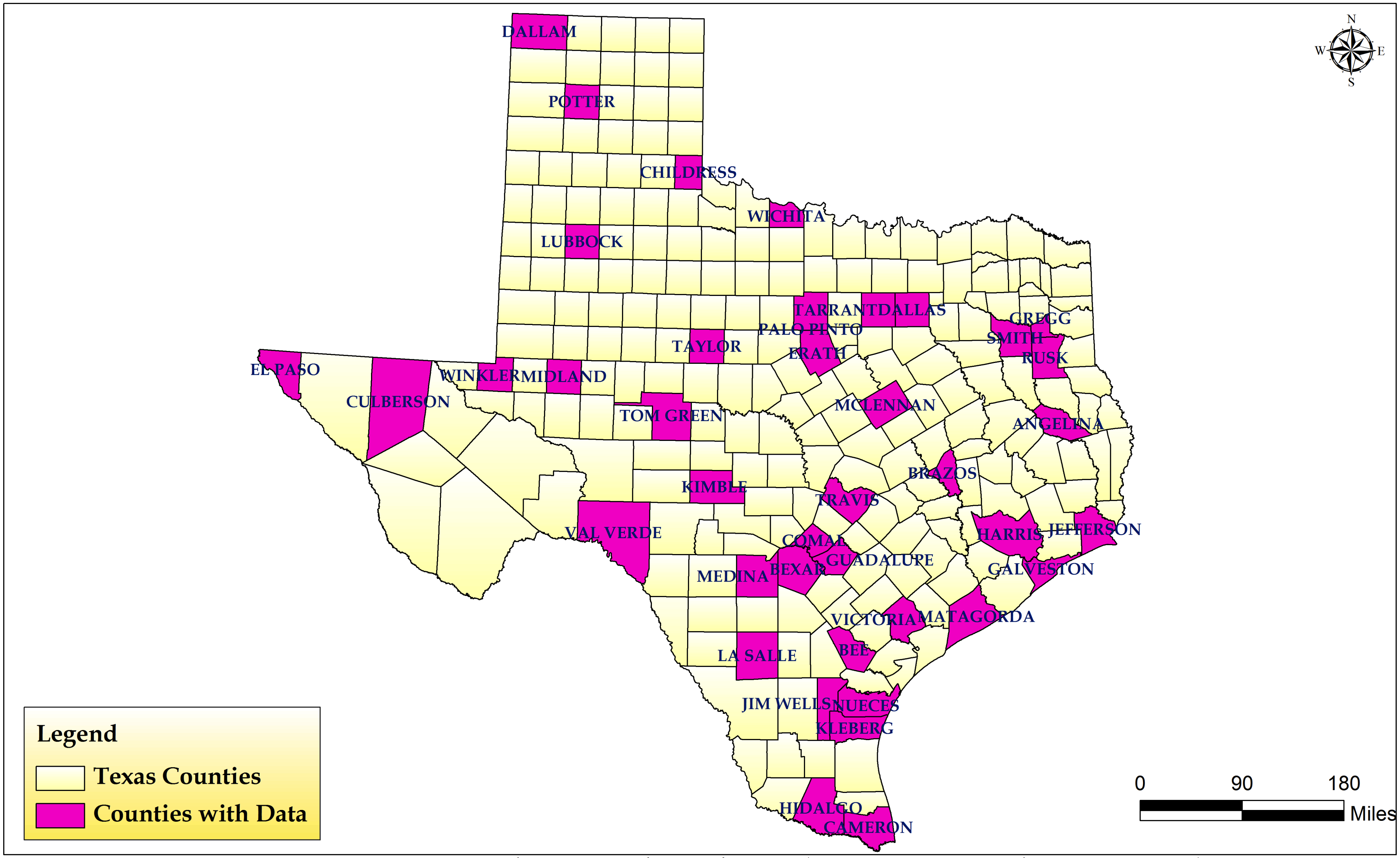

Figure 4.2: Texas counties with relatively long records (greater than 30 years) of meteorologic data availability.

5. GCM Selection Methods

The purpose of this chapter of the report is to present the methodology used to examine the suitability of GCM models for use in assessing climate change for Texas. In addition, selection of preferable GCMs for the Texas study areas presented in Chapter 4 is addressed.

Uncertainty in climate models is one of the most researched topics in the field of climate change. It is a well-established fact that uncertainties exist in the GCM predictions. These uncertainties can be attributed to climate sensitivity, modeling assumptions, or the assumptions made regarding the GHG emissions. The uncertainty attributed to climate sensitivity is defined as the uncertainty in the response of the Earth's climate to anything that causes change in the global energy balance. Uncertainty attributable to modeling assumptions is that arising from the approximations (parameterization) required for sub-grid-scale processes and model structure. Because the future generation of GHGs is uncertain, there are several emission scenarios and several different directions in which the long-term future climate can respond to these emissions. This issue defines the uncertainties in GHG emissions. Without detailed analysis of the input and output from a GCM, it is impossible determine which of the three sources of uncertainty dominates (if any do). However, irrespective of the nature of uncertainties, water resources planners need guidance on how to address the existing uncertainties and select the climate models while accounting for the inherent uncertainty in their projections.

As stated by Katherine Hayhoe (personal communication, February 24, 2012), it is not possible to predict a specific future climate with certainty. What the modelers can do best in given circumstances is develop a series of projections that capture the range of likely climate conditions. Several researchers provided recommendations for the process of GCM selection. These recommendations included the following.

1. Use of ensemble simulations (results developed by averaging results from multiple models instead of using results from one or two GCMs). It is the consensus of the climate-modeling community that the average of multiple models provides a better representation of potential future conditions than any one model.

2. Use models that are well-established, thoroughly researched, and extensively reported in peer-reviewed scientific literature.

3. Use models that represent large-scale climate features, such as atmosphere-ocean heat relations, atmospheric circulation patterns, and El Niño, that have an impact on regional climate. Perform a thorough study and determine the climate processes that drive the regional climate

for a given region, Use the GCM results to reproduce the climate process that impacts the region of interest and select those GCMs that perform better than others.

4. Use newer models or the models of the most recent generation. The model physics of the climate models are constantly updated and the newer models contain more representative physics compared to the previous generation models.

5. Use the average (ensemble) of as many models as possible within the constraints of the study. There is no magic number of number of models that should be used for averaging, and the number should be determined independently for each project based on the information applicable to the project.

6. Instead of recommending a "best" model, modelers should focus on removing or "culling" ineffective models after determining those model with the least skill for the region of interest.

7. Use a variety of models that best represent the wide range of the uncertainty in the future predictions.

Following the list of recommendations available from the literature review, the following methodology was developed for GCM selection for the State of Texas. The CMIP3 database contains a group of 25 available GCMs. From this group, 12 were selected because of their spatial resolution and the relative ease and extent of data availability. The GCMs suitable for Texas climate studies were selected from the list of 12 GCMs. The GCM selection included two sequential comparisons.

- GCM Performance. For the research reported herein, the term *GCM performance* is used to measure the ability of a GCM to reproduce certain observed atmospheric behaviors. The performance of a GCM was tested by comparing GCM output when driven using known (measured) meteorologic data to reproduce the observed behavior of a large-scale climate feature. National Center for Environmental Prediction's (NCEP) reanalysis data were used to represent the real-time behavior of the large-scale climate feature. Those GCMs that best reproduced the large-scale climate feature were chosen for the next comparison. The large-scale climate feature was identified through the literature review.

- GCM Convergence. A second measure of GCM suitability for use in assessing potential climate change for Texas is examination of GCM convergence. The term *GCM convergence* refers to a comparison of whether the output from a particular model compares to the output of other models when all are operated using the same input variables and (as appropriate) parameters. A climate projection can be regarded as any description of the future and the trajectory leading to it. However, a more specific interpretation is used with the term "climate projection" by the IPCC when referring to model-derived estimates of future climate. The convergence of the best performing GCMs was tested by comparing the GCMs projected surface temperature and precipitation variables for selected emission scenarios. These variables are necessary for production of downscaled RCMs, and similar, but not identical, GCM scenario outputs should lead to reasonable estimates of regional weather conditions.

Convergence between GCM results indicates that results from a variety of models are in general agreement on future trends. This desirable result demonstrates reduced uncertainty in model results, but not necessarily in the absolute outcome of the climate-change scenario. In contrast, a broad range of projections between models indicates increased uncertainty in future trends. Testing the range of projections is important because a large range in the model projections will point to uncertainty in future trends, while a narrow range in the model projections confirms that the models are in agreement with respect to future trends. Model selection for ensemble analysis can be determined by testing the range of the projections. "Ensembling" is the process of averaging results for a group of complementary models. Therefore, those models that converge best can be used for ensemble analysis. The models whose projections are on the upper or lower boundary of the range of projections can be used if the intent is to downscale high or low projections.

5.1. GCM Performance Analysis

Because of the scale of the models, GCMs are better at representing large-scale climatological or meteorological features than regional features. Therefore, the ability of GCMs to reproduce the observed performance of a large-scale climate feature can be used to select a preferable GCM for a given region. The first step in the GCM performance analysis was selection of the most appropriate GCMs. The 12 pre-selected GCMs are listed in Table 5.1. The next step was selection of the large-scale climate feature that most impacts the Texas climate (Section 5.1.1). Finally, the GCMs were tested for their abilities to replicate the actual behavior of the large-scale climate feature (Section 5.1.2).

5.1.1. Selection of Large-Scale Climate Features

The purpose of this section is to describe the process of selecting the large-scale features that should be used for assessing GCM performance in Texas. It is important to note the difference between large-scale climate features and smaller-scale weather variables. Meteorology refers to the atmosphere in general, climatology refers to long-term average weather conditions, and weather refers to the temporal variables we can measure at any time. The first step was to determine the large-scale climatic features defining the regional climate of the study areas. As explained earlier, the dependence of a region's climate on a large-scale climatic feature is known as teleconnection[1]. After the large-scale feature was identified, it was important to establish that a fluctuation in the large-scale climate feature does result in a corresponding fluctuation in the climate of the study site. The GCMs were compared based on visual fit to observe their representations of the large-scale features, and the most appropriate one was selected.

After detailed review of the available literature and analysis, it was observed that the polar jet stream exercised considerable impact on the climate of Texas. Oscillation of water temperature and global pressure/wind patterns across the Pacific Ocean have been caused by natural occurring cyclical changes in global circulation patterns for 100,000 years. These oscillations have both global

[1] Climate Prediction Center, `http://www.cpc.noaa.gov`, 2010.

Table 5.1: GCMs used in the GCM performance analysis.

No.	Originating Group(s)	Country	$CMIP_3$ ID	Cell Size (Lat/Long)
1	Hadley Centre for Climate Prediction and Research/Met Office	UK	UKMO-HadGEM1	1.25×1.875
2	National Center for Atmospheric Research	USA	CCSM3	1.4×1.4
3	CSIRO Atmospheric Research	Australia	CSIRO-Mk3.0	1.875×1.875
4	Max Planck Institute for Meteorology	Germany	ECHAM5/MPI-OM	1.875×1.875
5	US Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory	USA	GFDL-CM2.1	2.0×2.5
6	Institut Pierre Simon Laplace	France	IPSL-CM4	2.5×3.75
7	Hadley Centre for Climate Prediction and Research/Met Office	UK	UKMO-HadCM3	2.75×3.75
8	Meteorological Research Institute	Japan	MRI-CGCM2.3.2	2.8×2.8
9	National Center for Atmospheric Research	USA	PCM	2.8×2.8
10	Bjerknes Centre for Climate Research	Norway	BCCR-BCM2.0	2.8×2.8
11	Canadian Centre for Climate Modelling & Analysis	Canada	CCCMA-CGCM3.1(T63)	2.8×2.8
12	Météo-France/Centre National de Recherches Météorologiques	France	CNRM-CM3	2.8×2.8

and regional impacts. El Niño and La Niña, affect the location of the polar jet stream. Jet streams are "rivers of air" found at high altitudes and noted for their high speeds (NOAA). The polar jet stream moves north and south across North America. When the jet stream is in Canada, the weather to its south tends to be mild or at least less cold. When the stream swings further south into the United States in winter, very cold, often harsh weather prevails at the surface to the north of the jet stream. Zonal flow (flow in the west-east direction along the latitudes) in polar jet stream is more frequent during La Niña, which results in minimum undulations of jet streams in the north-south direction, which in turn divides warm air to the south of the jet stream from cold air to the north. La Niña thus causes drier weather conditions for Texas with less precipitation because the polar jet stream moves more north. Azonal flow or meridional flow (flow in the north-south direction or along the meridian) by the polar jet stream is more frequent during El Niño, such that jet streams are no longer parallel with the west-east direction but swing toward the north-south direction. Therefore, an El Niño causes precipitation increases in Texas because the polar jet stream moves farther south and brings more storm-causing conditions. The general conclusion is that El Niño (La Niña) years result in increased (decreased) precipitation levels and decreased (increased) temperature levels for United States. The sensitivity and conformity of Texas climate to this phenomenon was tested by conducting a sensitivity analysis as explained in Appendix A.

5.1.2. GCM Comparison Methodology

Selected GCMs were evaluated for their abilities to reproduce the real-time movement of the polar jet stream by a methodology developed Bradbury et al. (2002b). The GCMs comparison process was based on a visual comparison of seasonal variation of the latitudinal location of the polar jet stream. The details of Bradbury's research were discussed in Chapter 3. This method of GCM comparison is known as the Jet Latitude Index (JLI) method. The JLI was developed by Bradbury et al. (2002b) to understand the seasonal variation of the latitudinal location of the polar jet stream. Jet streams are known for their high speeds, with maximum wind speed at the core of the jet stream[2]. In meteorological practice, the core of the jet stream is best represented by the wind velocity recorded at 200 mb pressure level[3] and blowing from west to east. The 200 mb pressure level is selected because the presence of polar jets stream is strong at these pressure levels. JLI represents the monthly mean position of the polar jet stream based on the position of 200 mb zonal wind variable. The location of the polar jet stream is determined from the latitude of maximum zonal winds found within the latitudinal range covered by the study site. The JLI was computed as the average latitude of maximum zonal winds in the range of longitudes covering the study area.

[2]NOAA, 2010, see http://www.noaa.org

[3]Represents atmospheric pressure level. Pressure decreases with height and standard sea-level pressure is 1013 mb (1 millibar = 1 hectopascal = 100 pascals); 850 mb=1.5 km vertical elevation; 700 mb=3.0 km; 500 mb=5.5 km; 300 mb=9.0 km; 250 mb=10.5 km; 200 mb=12.0 km.

GCM Performance — Model Setup

A program was developed to perform the JLI analyses. The analyses were performed for the five study areas established for the project at the following geographical locations in Texas: north, east, south, west, and far west. The latitude and longitude ranges for the study areas and used in the JLI model are presented in Table 4.1 in Chapter 4. The boundaries of the study areas used to perform the JLI analysis are presented in Figure 4.1 in Chapter 4.

The JLI program was run using an analysis platform called IDL[4]. IDL is a visual tool used to manipulate data and create meaningful visualizations from complex numerical data. The software was used with each the 12 selected GCMs, the reanalysis dataset, and using data from latitude/longitude grids for the five study areas. The study period of record used in the JLI analysis was a historical time-period of 30 years (1970–2000). Real-time observations representing the location of center of the polar jet stream were obtained from the NCEP/NCAR reanalysis dataset[5] (NCEP). The NCEP dataset is a continually-updated gridded dataset representing the state of the Earth's atmosphere, incorporating observations and numerical weather prediction (NWP) model output dating back to 1948. It is a joint product from the National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR). The JLI was computed by calculating the latitude value for the maximum wind velocity from the 200-mb wind data for both the GCM datasets and NCAR reanalysis dataset each month over the 30-year period over the longitude range for each study site. Finally, average monthly JLI values were calculated. Some screening procedures were built into the JLI identification program. The purpose of the screening procedures was to help identify odd occurences of JLI and eliminate months with these occurences. For some months, a strong and singular regional jet stream was not clearly identifiable. These months were not included in the JLI analysis. Analysis for some other months resulted in more than one jet. Jet streams are fast flowing, relatively narrow air currents found in the atmosphere around 7 miles above the surface of earth. For a given month, there can be only one average latitudinal location with strong wind currents. If a given month has more than one jet, that suggests error in the data set for that month and hence the data for that month was not included in the analysis for the calculation of the latitudinal location of jet stream. For any given month, the JLI was not assigned if the observed maximum zonal wind velocity at one longitude was greater than 12° north or south from the maximum zonal wind velocity observed at any other longitude. If the latitudinal locations are 12°apart, the JLI at two longitudes might be referring to two different maximum wind currents and not the same one. These automated screening procedures were proven to be effective at removing most months lacking a clearly distinct jet or having more than one predominant jet within the index domain.

[4]The IDL website is `http://www.exelisvis.com/IDL` at the time of this writing.
[5]The NCEP website is `http://www.ncep.noaa.gov` at the time of this writing.

Table 5.2: GCMs selected from JLI and NCEP reanalysis data by study area.

Study Area	Region	GCMs Selected
Study Area 1	Eastern	CCSM, GFDL, BCCR, CNRM
Study Area 2	Southern	CCSM, GFDL, BCCR, CNRM, HADCM, PCM, ECHAM, CGCM, IPSL
Study Area 3	Western	CCSM, GFDL, BCCR, CNRM
Study Area 4	Northern	CCSM, GFDL, BCCR, CNRM, HADCM, PCM, CSIRO
Study Area 5	Far West	GFDL, CNRM, CSIRO, CGCM

GCM Performance — Results

The JLI was developed for the project study areas. Examples of results from the GCM performance analysis[6] are presented in Figures 5.1 and 5.2. Two plots were developed for each study area. The first set of plots (before) presents the comparison trends for all climate models considered, the model-ensemble, and the reanalysis dataset. The model ensemble is computed by averaging the GCM model data. Monthly location of jet stream for climate models are represented by different shapes and colors. Real-time representation of the jet stream location by NCEP/NCAR reanalysis dataset is indicted by means of a red line with grey range bars (+/- 5%). Model ensemble is shown by means of a black dotted line. The second set of plots (final selected) contain comparison trends for only those climate models whose trends compared well with the reanalysis dataset trends. Each point on the plot represents the 30-year average of the latitudinal location of the polar jet stream for a given month, averaged over the longitude range covering the domain of the study area. Those climate models with JLI trends closer (within 4° latitude) to the JLI trend for the reanalysis dataset (red line) were selected as models that best reproduced the location of the polar jet stream for the period of record. Results from the climate models in the second plot represent those best suited for the given study area as reflected by their ability to reproduce the location of the polar jet stream. Details of climate models selected for each of the study areas are presented in Table 5.2. These climate models represented large scale climate features (jet streams) better than other models. Based on the results obtained from the JLI analysis, these climate models were short-listed for GCM Convergence analysis.

The models listed in Table 5.2 were chosen because they performed better than the other GCMs in their ability to reproduce the fluctuations of the polar jet stream. Projections from any of these models can be used for climate-change downscaling studies in Texas. As discussed in Section 5.1, using the average of multiple models (the ensemble) results in a solution considered superior to that from a single "preferable" model. Therefore, an average of all the climate models from Table 5.2 should be used for performing downscaling studies. The primary goal of the GCM performance analysis was to select those GCMs that produce superior representation of the global scale features of import to Texas. Results from the analysis presented in this report supports selection of the models presented in Table 5.2.

The next step is to compare the ability of selected models to predict future climate and determine

[6] The complete set of figures are presented as Figures B.1–B.10 in Appendix B.

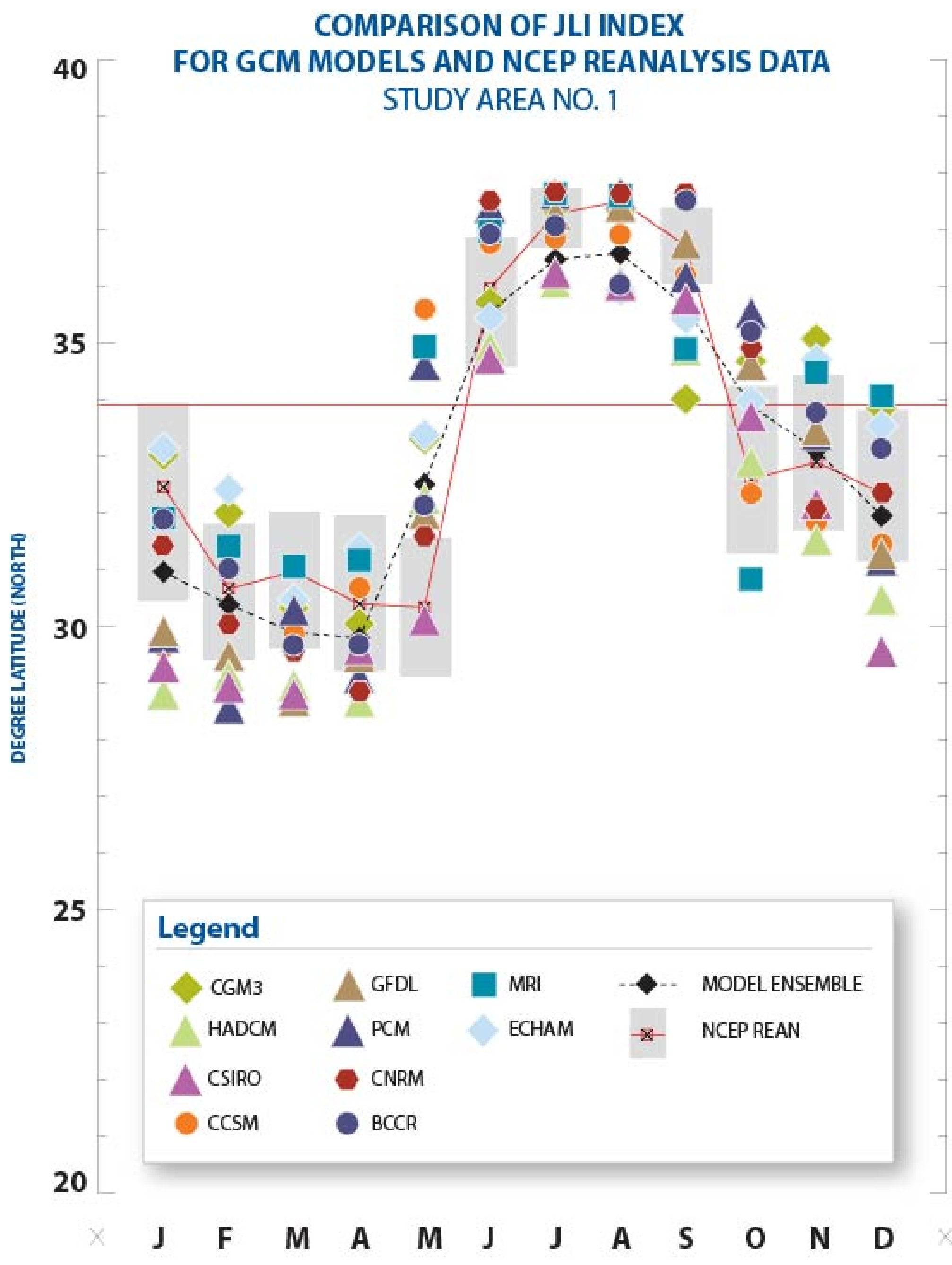

Figure 5.1: Comparison of JLI for GCM models and NCEP reanalysis data, Study Area Number 1.

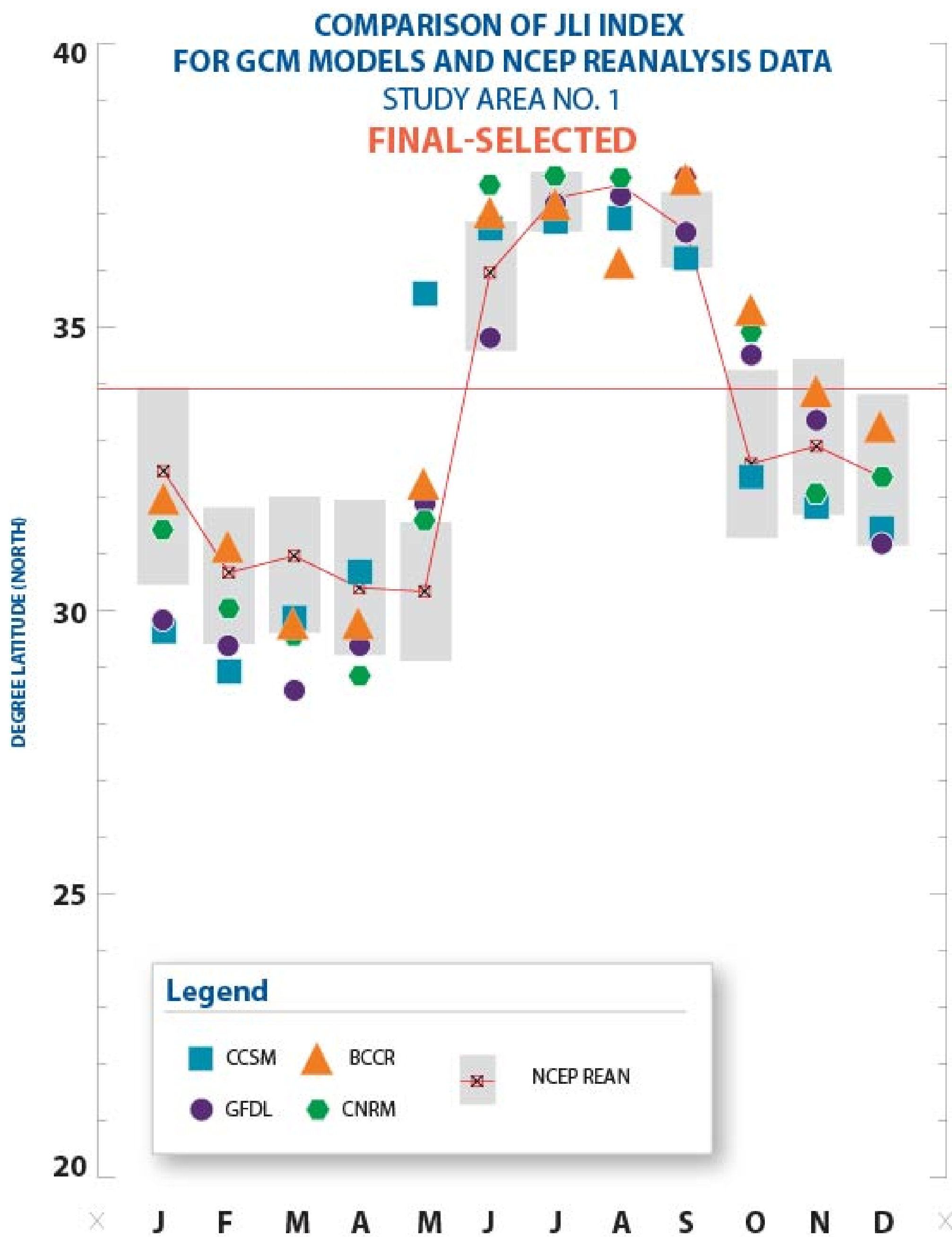

Figure 5.2: Comparison of JLI for GCM models and NCEP reanalysis data, selected models for Study Area Number 1.

the range of predictions. GCM convergence analysis was used to examine the predictive capabilities of selected models. From Table 5.2, it can be noted that two models were common for all five study areas (GFDL 2.1 and CNRM-CM3) and two other models (BCCR BCM 2.0 and CCSM 3.0) were common to four of the five study areas. Based on literature review (Lin et al., 2006; Zhang et al., 2003), it was noted that these four models were extensively used by other researchers in US and the models produced superior results for other regions in US. It was also noted that the model output was updated at regular intervals and the GCMs were maintained current. Even though one climate model (CCSM 3.0) did not produce good results for study area 5, the four models were selected based on the results of the GCM performance analysis and other reasons mentioned above and are believed to be adequate for further analysis (GCM convergence analysis). Therefore, the four models (CNRM CM 3.0, GFDL 2.1, BCCR BCM 2.0, and CCSM 3.0) were chosen for GCM convergence analysis. Convergence among models indicates that output from those GCMs is in general agreement on the future trends. A wide range of projections among models indicates uncertainty in the future trends. It is important to include climate models that represent the greater part of the range of uncertainty, which means all the GCMs that can be used for a given region based on GCM performance should be considered for downscaling studies. However, it is important to examine the range of projections for each of the climate models to understand the differences between potential outcomes as predicted by each model.

5.2. Descriptions of GCMs Selected in GCM Performance Analysis

A brief description of the GCMs selected in the GCM performance analysis and used in GCM convergence analysis is provided in the paragraphs below.

5.2.1. CCSM 3.0

CCSM is a coupled climate model composed of four separate models simulating the earth's atmosphere, ocean, land surface, and sea-ice. It has one central coupler component. The CCSM project was a cooperative effort of several climate researchers and was supported by the National Science Foundation (NSF), NCAR, Department of Energy (DOE), and the National Aeronautics and Space Administration (NASA). The atmospheric model is the Community Atmosphere Model (CAM), a global atmospheric GCM developed from the NCAR CCM3. The model grid has a horizontal resolution of 128 longitudinal by 64 latitudinal points with 26 vertical levels. The oceanic model is an extension of the Parallel Ocean Program (POP) Version 1.4.3 developed by Los Alamos National Laboratory (LANL). The horizontal resolution of the model is 1° latitude by 3.6° longitude with 40 vertical levels (Vertenstein et al., 2004).

5.2.2. GFDL 2.1

GFDL CM 2.1 is a coupled atmosphere, land, and ocean model. This climate model was developed by the Geophysical Fluid Dynamics Lab. GFDL 2.1 is a grid point model with a horizontal resolution of 2° latitude by 2.5° longitude for atmosphere and land components and 1° latitude by 1° longitude for ocean regions. The vertical resolution of the atmospheric and oceanic components is 24 layers[7].

5.2.3. BCCR BCM 2.0

BCCR BCM 2.0 is a coupled model with atmosphere/land, and ocean/sea ice components. This climate model was developed by the Bjerknes Centre for Climate Research at University of Bergen, Norway. BCM 2.0 is a grid point model with a horizontal resolution of 2.8° latitude by 2.8° longitude for atmosphere and land components. The vertical resolution of the atmospheric component is 31 layers[8].

5.2.4. CNRM CM 3.0

The CNRM-CM3 global coupled system is the third version of the ocean-atmosphere model initially developed at CERFACS, Toulouse, France, then regularly updated at Center for National Weather Research (CNRM), METEO-FRANCE, Toulouse. CNRM CM3 is a grid point model with a horizontal resolution of 2.8° latitude by 2.8° longitude for atmosphere and land components. The vertical resolution of the atmospheric component is 45 layers (Salas-Mèjia et al., 2005).

5.3. GCM Convergence Analysis

The GCM performance analysis tested the ability of selected climate models to reproduce the location of the polar jet (a large-scale climate feature of importance to Texas climate). However, in addition to testing model performance, it was also important to determine the range of the weather variable predictions by each GCM. A projection can be regarded as any description of the future and the trajectory leading to it. However, a more specific interpretation has been attached to the term "climate projection" by the IPCC when referring to model-derived estimates of future climate. The range of projections was tested by means of GCM convergence analysis. The section below presents details of the GCM convergence analysis. The methodology is discussed in Section 5.3.1 and a discussion of the results is presented in Section 5.3.2.

5.3.1. GCM Comparison Methodology

The purpose of this analysis is to compare the range of projections predicted by the GCMs chosen based on the GCM performance analysis. GCM projections were compared using average precipi-

[7] Information about the GFDL GCM is available from the project website, which was `http://www.gfdl.noaa.gov` at the time of this writing.

[8] Information about the BCM 2.0 GCM is available from the project website, which was `http://www.bcm.uib.no` at the time of this writing.

tation and average temperature because these variables are the most easily available variables for all climate models and also the most important ones for water resource planners. In this analysis, cumulative precipitation ("pr") in the GCM output was used to represent the precipitation variable and 2 m air temperature ("tas") was used to represent the temperature variable. To compute future projections for each month, precipitation and temperature values for years 2036–2065 were averaged for the latitude/longitude grid covering the study area. Similarly, precipitation and temperature averages for years 1970-2000 were used to represent the historic 30-year average. Monthly values of future and historic averages were plotted to display the annual trends.

Furthermore, seasonal averages from different climate models were compared to estimate the range of projections. The averages were computed for four seasons: winter (December, January, February), spring (March, April, May), summer (June, July, August), and fall (September, October, November). To simplify the comparison process, GCM projections for a historic 30-year period were subtracted from GCM output for the future 30-year period. This test was conducted for the four climate models that were commonly selected for the five study areas. The list of climate models selected based on GCM performance analysis are listed in Table 5.2.

5.3.2. GCM Convergence Results

Plots of annual precipitation trends from the GCM projections for future and historic 30-year periods are included as Figures C.1–C.5 in Appendix C. An example of the results is presented in Figure 5.3. Each point on these plots represents monthly precipitation (inches/month) averaged over a 30-year period (historic: 1970–2000, future: 2036–2065) and covering the latitude/longitude grid defining the study area.

Similar plots of the annual temperature trends were prepared and are included as Figure C.6–C.10 in Appendix C. An example is presented as Figure 5.4. Each point on these plots represents monthly temperature (°F) averaged for a 30-year period (historic: 1970–2000, future: 2036–2065) and covering the latitude/longitude grid defining the study area.

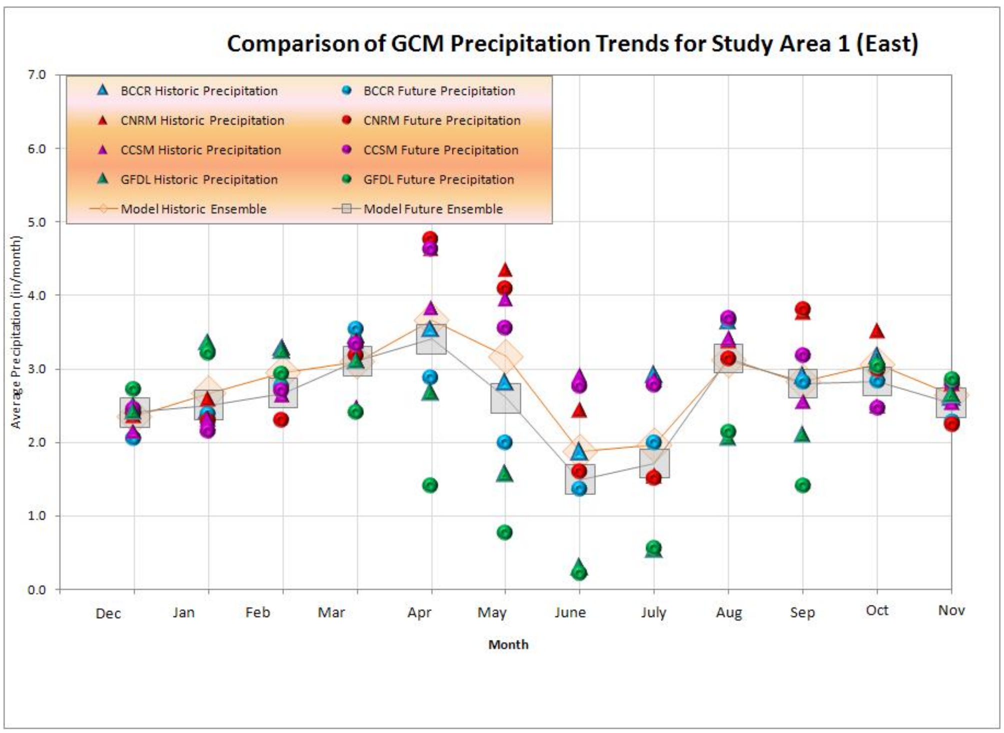

Figure 5.3: Comparison of GCM precipitation trends for Study Area 1 (East).

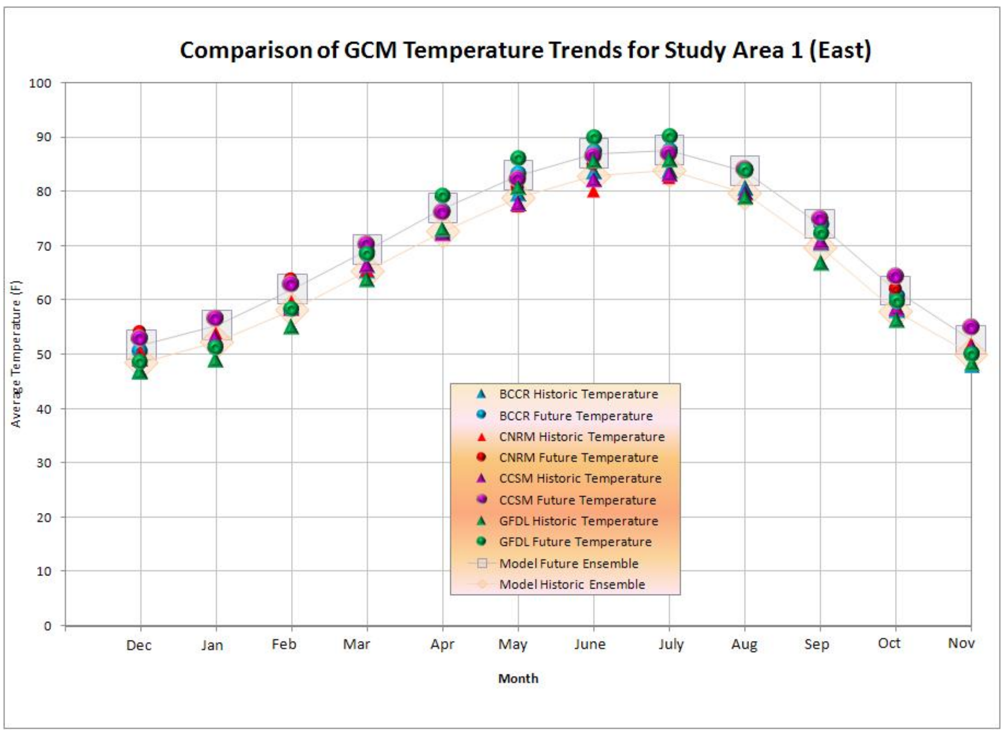

Figure 5.4: Comparison of GCM temperature trends for Study Area 1 (East).

The models generally tended to agree better in terms of their projections of temperature than for precipitation. An agreement was identified if the model projections were in similar direction when predicting the future trend (increase or decrease in the future value) and if the difference between future and historic projections for a model was within 0.6 inch/month for precipitation values and 3°F for temperature values (threshold values selected by researchers and represent approximately 30% of the maximum values). This result validates the general conclusion drawn by several climate researchers (Lin et al., 2006; Zhang et al., 2003) about GCM capabilities with respect to temperature and precipitation projections. The model physics involved in the temperature computations were appropriate to the scale of the GCM models. However, the resolution of the convection scheme is finer than the scale at which the GCMs are run, and hence the precipitation values are subject to the assumptions inherent in the representation of the convection scheme.

Seasonal comparison plots for precipitation and temperature are presented as Figures C.11–C.20 in Appendix C. Examples are presented as Figures 5.5 and 5.6. To determine the projection trend of precipitation and temperature, the GCM predictions for the historic period were subtracted from the GCM predictions for the future period. Temperature results from the climate models were superior to precipitation results. The climate models predicted temperature increases in the range of 3–8°F for the future period (2036–2065) relative to the historic period (1970–2000). Climate models GFDL, CNRM, and BCCR produced similar results for the precipitation trends. These climate models predicted precipitation decreases ranging from 0.2–0.8 inches per month for the future period (2036–2065) when compared to the historic period (1970–2000). Results from CCSM range from a minor decrease (≈0.2 inches per month) to a strong increase (≈0.8 inches per month) in the future precipitation.

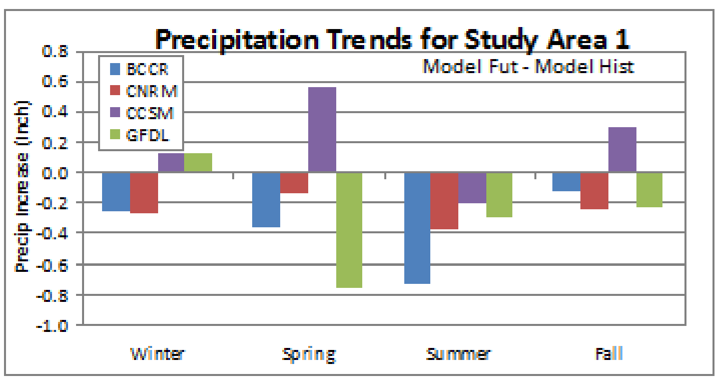

Figure 5.5: Comparison of GCM precipitation trends for Study Area 1 (East).

Therefore, based on the results of GCM convergence analysis, the GFDL CM2.1, BCCR BCM 2.0, and CNRM-CM3 models produced similar solutions and can be used for ensemble analysis. The projections for CCSM 3.0 model depart from the other models. The CCSM model can be included

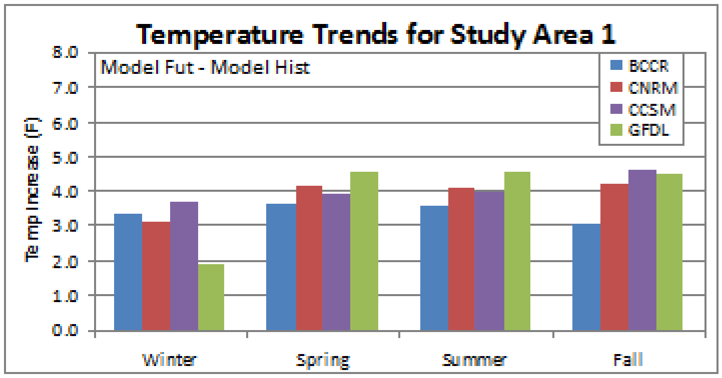

Figure 5.6: Comparison of GCM precipitation trends for Study Area 1 (East).

in the ensemble (because the recommendation is to use models that represent the greater part of the future uncertainty), but the departure of CCSM 3.0 projections should be noted when using the model for climate change analysis.

6. Conclusions and Recommendations

6.1. Summary

The objectives of this research project were

1. To develop a method or methods for assessing General Circulation Model (GCM) results as appropriate for Texas climate,
2. To use that result or results to censor the suite of available GCMs and select those most appropriate for assessing potential climate change in Texas,
3. From the suite of selected GCMs, examine the results and recommend further applications, and
4. Examine the literature to determine an appropriate approach for downscaling GCM results for application to Texas water resources management.

Twelve GCMs were selected from a suite of 25 available GCMs for evaluation based on their superior model resolution and data availability. The skill of the selected 12 GCMs to reproduce the fluctuations of the polar jet stream, a large-scale climate feature that impacts the climate of Texas, was tested. The basis of measurement was the Jet Latitude Index (JLI). The JLI represents the monthly mean position of the polar jet stream based on the position of 200 mb zonal wind (high speed) variable. Four GCMs demonstrated acceptable skill in representing the polar jet stream as measured by the JLI. These four models were compared using a process called "convergence" to determine whether the selected models produce a suite of consistent results. That consistency defines convergence and it helps to provide insight into the range of uncertainty in projected future trends.

Downscaling is the process of converting GCM output, which represents a relatively large geographic area or scale, to a scale appropriate for use in water resources and hydrologic applications. The literature was examined for approaches to downscaling GCM results. The methods identified included the climate factor approach, dynamic downscaling (regional climate modeling), and statistical downscaling. Statistical downscaling approaches were further broken into two groups: [1] use of statistical relations between historical gridded observations and GCM historical-period results to rescale GCM future-period results to be consistent with observed climate and [2] weather generators. For application to Texas water resources management studies, the bias-corrected statistical downscaling approach is recommended. Weather generators are interesting from a stochastic modeling perspective, but are probably not of principal interest to Texas water resources planners.

6.2. Conclusions

The following conclusions were developed from the study results.

- The study was conducted for one GHG emission scenario, SRES A1B. The A1B scenario is a moderate emission scenario when compared to other scenarios and was selected because it provides a balanced (mid high/mid low) representation of a future impacted by climate change.
- GCM selection in this study was carried out by means of GCM performance analysis and GCM convergence analysis.
  - The performance of GCM predictions was tested by comparing the GCM skill in reproducing historical behavior of a large-scale climate feature. Historical behavior is obtained by processing measured meteorological observations through the candidate GCM. This process is called "reanalysis" and is used by climate researchers for model validation (among other things). NCEP's reanalysis data were used to represent the historical behavior of the large-scale climate feature.
  - The range of weather variable projections by GCMs was tested. A projection can be regarded as a description of future climate and the trajectory leading to it. The convergence of the best performing GCMs was tested by comparing model-predicted surface temperature and precipitation for selected emission scenarios. These variables are of interest in assessing the potential impact of climate change. Similar, but not identical, GCM scenario outputs should lead to reasonable projected ranges of regional weather conditions.
- Twelve GCMs (out of 25) were selected in an initial review based on superior model-resolution and data availability for a GCM performance analysis.
- The polar jet stream, which traverses the continental United States from west to east, exerts a measurable influence on Texas climate and was chosen as the large-scale climate feature for assessing the GCM performance.
- From the initial candidate list of 12 GCMs, 4 were selected based on their skill in reproducing historical fluctuations of the polar jet stream. These models were: GFDL CM2.1, BCCR BCM 2.0, CCSM 3.0, and CNRM-CM3.
- Convergence between model results is an important component of quality assurance/quality control of GCM selection. Convergence between GCM-predicted variables indicates that the models are in general agreement on the future trends. A narrow range in model projections confirms that the results of the different models can be averaged through an ensemble analysis.
- GCM convergence was studied by testing the range of model projections. The projections averaged over a historical 30-year period were subtracted from the model projections for a future 30-year period to compare the projected future trends to the historic values. Variability

in long-term monthly projections of average precipitation was greater than variability in long-term monthly projections of average temperature.

  - Trends in long-term monthly projections for average precipitation were more variable between the models than the trends in long-term monthly projections of average temperature. Atmospheric convection responsible for precipitation occurs at a scale too small compared to the GCM solution domain and is a limitation in precipitation projections for most most climate analyses. In general, atmospheric processes that produce precipitation are not resolved for the scales used in GCM computations. Therefore, GCMs generally do not predict precipitation well. This inability of GCMs to resolve the convection that generally produces precipitation is a common limitation observed in most climate analyses.
  - Trends in the projected temperature occur at a scale much greater than that of precipitation and can be resolved by GCM algorithms. Therefore, results for temperature values and trends are generally better than those for precipitation.
  - Conclusions from GCM convergence analysis suggested that GCMs GFDL CM2.1, BCCR BCM 2.0, and CNRM-CM3 projected decreases in future precipitation, and CCSM 3.0 projected an increase. All four climate models projected an increase in future temperature. The results obtained for precipitation and temperature variables were in general agreement with conclusions developed by other researchers regarding the long-term impacts of climate change on Texas.

- Based on the results of GCM convergence analysis, the GFDL CM2.1, BCCR BCM 2.0, and CNRM-CM3 converge toward similar projections, while precipitation projections for the CCSM 3.0 model differ from the other three. When trying to obtain the climate data for the "most likely" future conditions, all four models should be included in the ensemble to represent greater overall uncertainty, but the difference of CCSM 3.0 projections should be noted.

- Two principal methods for downscaling are in current use. They are dynamical downscaling, in which a regional climate model is used, and statistical downscaling, in which historical observations (usually grid averages) are used to rescale GCM output.

  - Dynamic downscaling is not commonly used for hydrologic or water resources studies.
  - Statistical downscaling is most commonly used to provide the input to hydrologic and water resources models.
  - A third category, weather generators, can be used to generate suites of potential meteorologic sequences through stochastic simulation based on GCM projections and historical statistics.
  - A large number of downscaled (and bias-corrected) projections are available from the UCRL website. The development and documentation of these datasets is described in Section 3.5.

- When water planners in any region in Texas are looking for guidance on downscaling methodology, it is recommended (based on the literature review conducted in this study) that they use statistical downscaling.
- Projections from the suite of models selected in this study are suitable for regional downscaling in Texas. When water planners in any region in Texas are looking for guidance on selecting GCMs for downscaling climate analysis, it is recommended (based on the results of the analysis performed in this study) that they use an ensemble of downscaled data from climate models GFDL CM2.1, BCCR BCM 2.0, CNRM-CM3, and CCSM 3.0.

6.3. Recommendations

The following recommendations are developed based on the results reported in this report.

1. Regarding use of GCM output.
   (a) Use of ensemble results from GCMs is appropriate.
   (b) Although attractive to modelers accustomed to use of hydrologic and hydraulic models, use of output from a single GCM is not appropriate as it does not capture the variability in future uncertainty.
   (c) The large scale of GCM solutions produces results not directly comparable to ground-based observations.
   (d) Use of GCM results that are extensively reviewed in the professional literature is appropriate.
   (e) Use of GCM results proven to reliably represent large-scale climate features (such as the polar jet stream) is appropriate.
   (f) Development of GCM algorithms and code continues. Therefore, use of more recent results (GCM or downscaled GCM output) is preferable to results (GCM or downscaled GCM output) from the previous generation of GCMs.
   (g) Use of GCMs that preserve large-scale climatic features but produce different projections of future climate is useful in assessing the uncertainty of climate projections.
   (h) Definition of a single "best" GCM is not possible at this time. Therefore, energy should be focused on culling those models that do not represent the climate in the study area. (This task was done in the selection of recommended GCMs for this project.)
   (i) Uncertainty in future climate is represented by a suite of GHG scenarios. These scenarios contain assumptions about the impact of social, economic, demographic, and ecologic practices.
2. Regarding GCM scale.
   (a) Climate change projections using GCMs are probably more reliable on a global scale than at local or regional scales.

(b) The scale of GCM computations is such that climate change projections are not directly usable for regional or local impact assessment. Downscaling is required to obtain estimates for such studies.

(c) Statistical downscaling using gridded data and bias correction is most often used to obtain estimates of meteorologic variables used in water resources and hydrologic modeling. Statistical downscaling is recommended as the most suitable methodology for downscaling efforts in Texas.

(d) Downscaled results are generally provided for the GCMs recommended herein by `http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/dcpInterface.html`.

(e) Temporal distributions are generally at intervals not less than six hours. Therefore, further disaggregation of downscaled estimates are usually required.

6.4. Further Work

Although the results from the research presented herein can provide guidance on which GCMs are appropriate for Texas climate-change assessments, much work remains to be done to obtain results usable in water resources and hydrologic models. Because the State's WAM is based on naturalized streamflow, results from downscaled GCM output is not directly usable for water resources and hydrologic modeling in Texas. Additional work remains to be done, as presented in the discussion below.

1. The results produced in this study are a first step in developing mechanics for assessing the potential impact of climate change on Texas water resources.

2. It is important to use appropriate GCMs as ensembles for initiating climate studies for a region and also important to use GCM data downscaled to the regional or watershed level. As a next logical step, data downscaled to regional extent should be collected for the GCMs selected in this study. Several research organizations offer downscaled data for different regions in the United States and those data are readily available for use.

3. For regional downscaling studies, it is recommended to use an ensemble approach to average the downscaled GCM data for the models selected in this study instead of selecting one or the other models.

4. The downscaled information currently available is not directly usable in the State's WAM by Texas water resources engineers. An interface between the projected climate variables and WAM is required. The downscaled GCM data should be input to a hydrologic model (such as VIC). The output from the hydrologic model can then be input to the WAM.

5. A hydrologic model is essentially a water balance that accepts the future climate variables as inputs to a given watershed and predicts naturalized streamflows as outputs. The future climate-induced naturalized streamflows can then be used as inputs into the WAM to determine the available water supplies for a future climate scenario. The hydrologic model could

also be used to generate input variables such as evapotranspiration rates and recharge rates to drive the WAMs and groundwater availability models for future climate scenarios.

6. When water planners need to use the downscaled GCM results for impact studies, it is recommended that the downscaled GCM results (for GCMs selected in this study) be combined and then one set of ensemble results run through a hydrologic model or any other model in order to identify impacts on water supply.

7. The currently-available downscaled datasets described in Section 3.5 are at a spatial resolution of 1/8°. Temporal resolution of the downscaled datasets is monthly or daily. If a finer temporal resolution is required, custom datasets will be needed.

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A. El Niño, La Niña, and the Southern Oscillation

On conducting a detailed review of the literature available, it was observed that the jet streams exercised considerable impact on the climate of northwest Texas. *The general conclusion is that El Niño (La Niña) years resulted in increased (decreased) precipitation levels and decreased (increased) temperature levels for United States.* The sensitivity and conformity of northwest Texas climate to this phenomenon was tested by conducting a sensitivity analysis as explained below.

A study of the impact of El Niño—Southern Oscillation (ENSO) on Texas climate was conducted. The main focus of the study was to understand the sensitivity of Texas climate to ENSO-related teleconnections before proceeding to the comparison analysis of GCM-generated jet stream movement with actual jet stream movement. The variations in average temperature and precipitation anomalies during El Niño and La Niña years have been analyzed.

The climate data for counties outlined in the study areas section were collected. The surface daily data for precipitation, maximum, and minimum temperature were obtained from the NOAA data source. The analysis was focused on the period-of-record 1948–2009. The daily data were first converted to monthly data by calculating the monthly averages, and later the monthly values were manipulated to represent seasonal (spring, summer, fall, and winter) variations. *Seasonal precipitation and temperature anomalies for each year were calculated by subtracting the seasonal average for the entire period of record from that year's seasonal averages.*

These seasonal temperature and precipitation anomalies were sorted into El Niño and La Niña years by comparing the seasonal anomalies with ENSO climate indices. The climate indices were formulated in an attempt to characterize and understand the various climate mechanisms that culminate in our daily weather. The Bivariate ENSO Time series (BEST) were chosen for the comparison analysis. The BEST values were calculated from combining a standardized Southern Oscillation Index (SOI) and a standardized Niño 3.4 sea surface temperature (SST) time series. These climate indices were collected for the period-of-record with available climate data (1948–2009).

The ENSO indices (time series) were available at monthly frequencies. For each year, seasonal averages of the time series were manually calculated. A seasonal climate index value greater than 0.4 implied an El Niño season and an index value less than -0.4 implied a La Niña season. The index values between 0.4 and -0.4 indicated a neutral season (neither El Niño nor La Niña).

The seasonal precipitation and temperature anomalies were compared with seasonal climate indices, and the seasons were sorted into El Niño, La Niña, and neutral seasons. For example, if the climate index (0.5) for summer of 1993 indicated an El Niño season (index is greater 0.4 therefore El Niño), the precipitation anomaly for that summer contributed to El Niño anomaly. The average of El Niño, and La Niña seasonal anomalies for all years in the period of record was calculated. The increasing/decreasing trends in average anomalies of precipitation and temperature for the entire period of record were plotted. The trends in precipitation anomalies were studied to verify if the variations conformed to those expected from the impact of jet streams.

The summary results are presented in Figures A.1–A.6. The results of the sensitivity studies confirmed a pronounced influence of jet streams on all study areas used to represent the climate of Texas. It can be noticed that El Niño (La Niña) years resulted in increased (decreased) precipitation levels and decreased (increased) temperature levels.

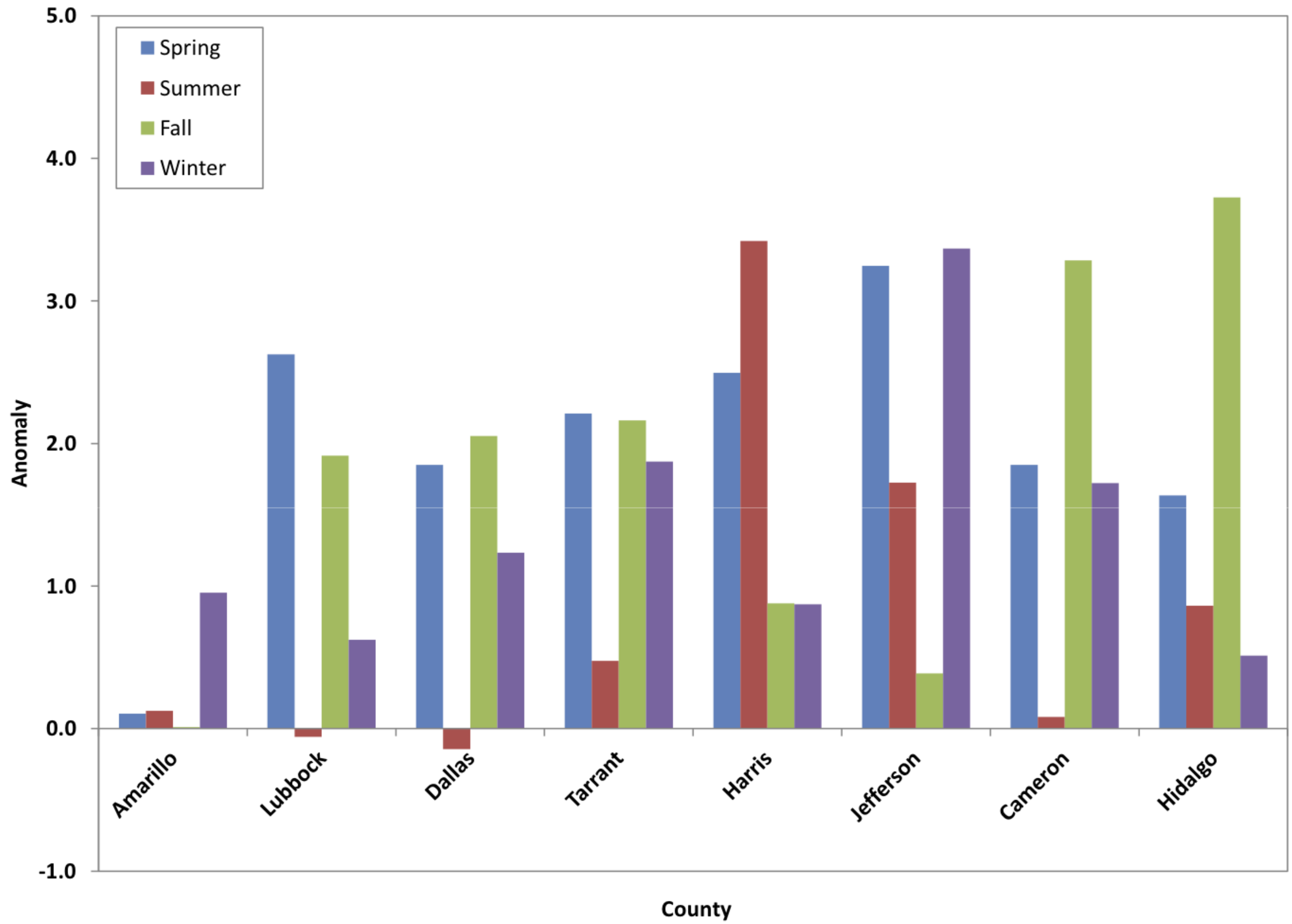


Figure A.1: Precipitation anomalies during El Niño years for study area counties.

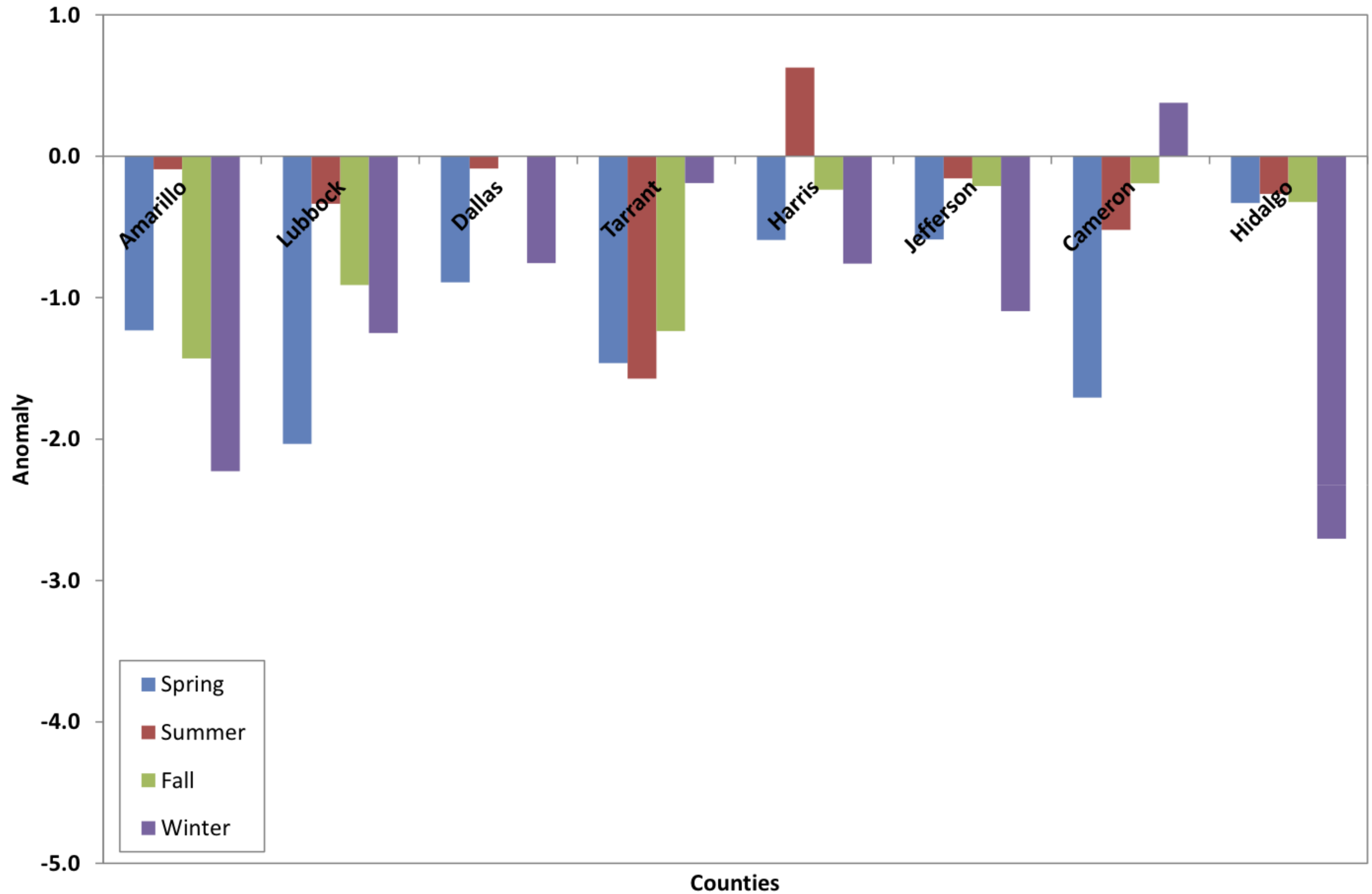


Figure A.2: Maximum temperature anomalies during El Niño years for study area counties.

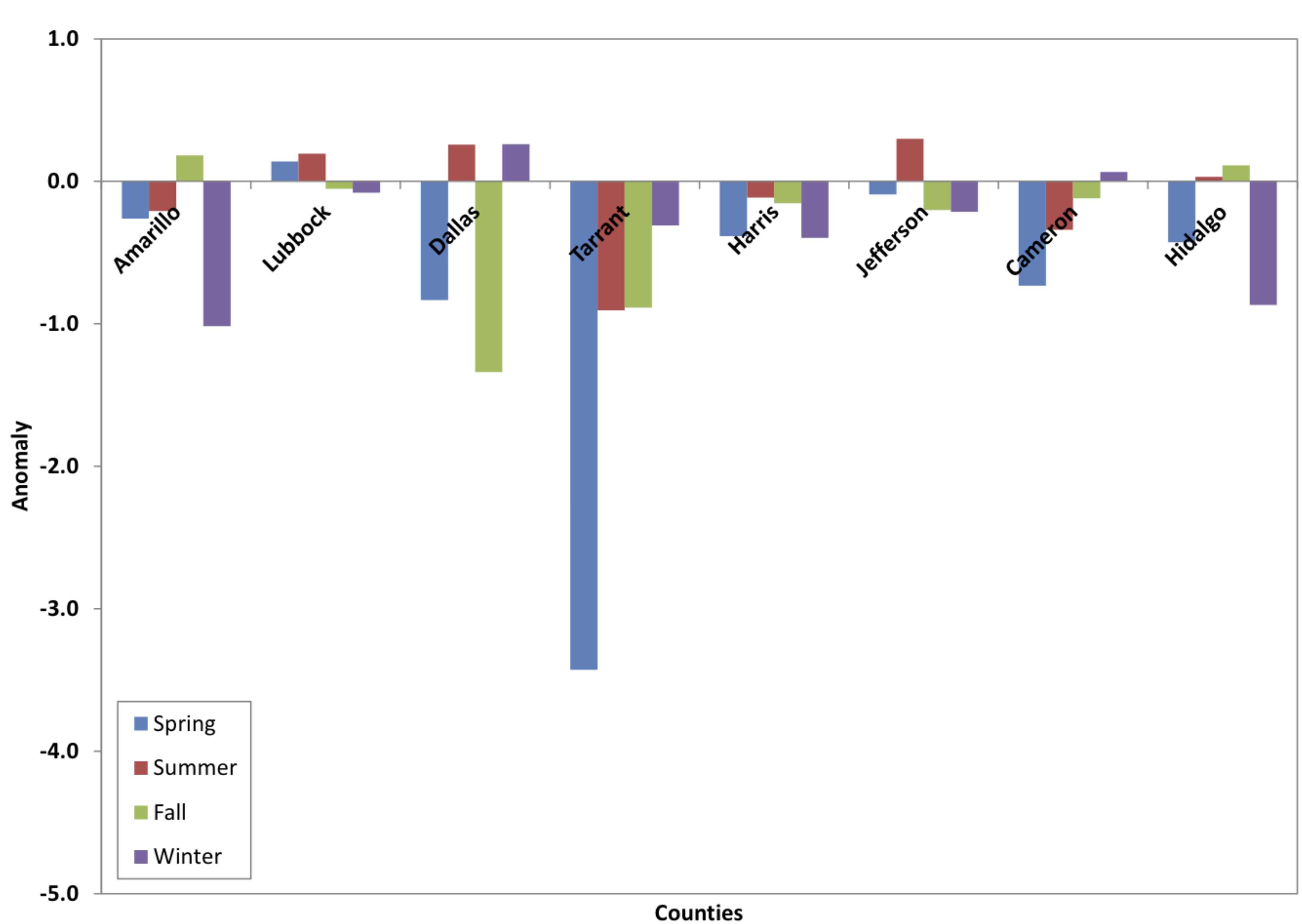


Figure A.3: Minimum temperature anomalies during El Niño years for study area counties.

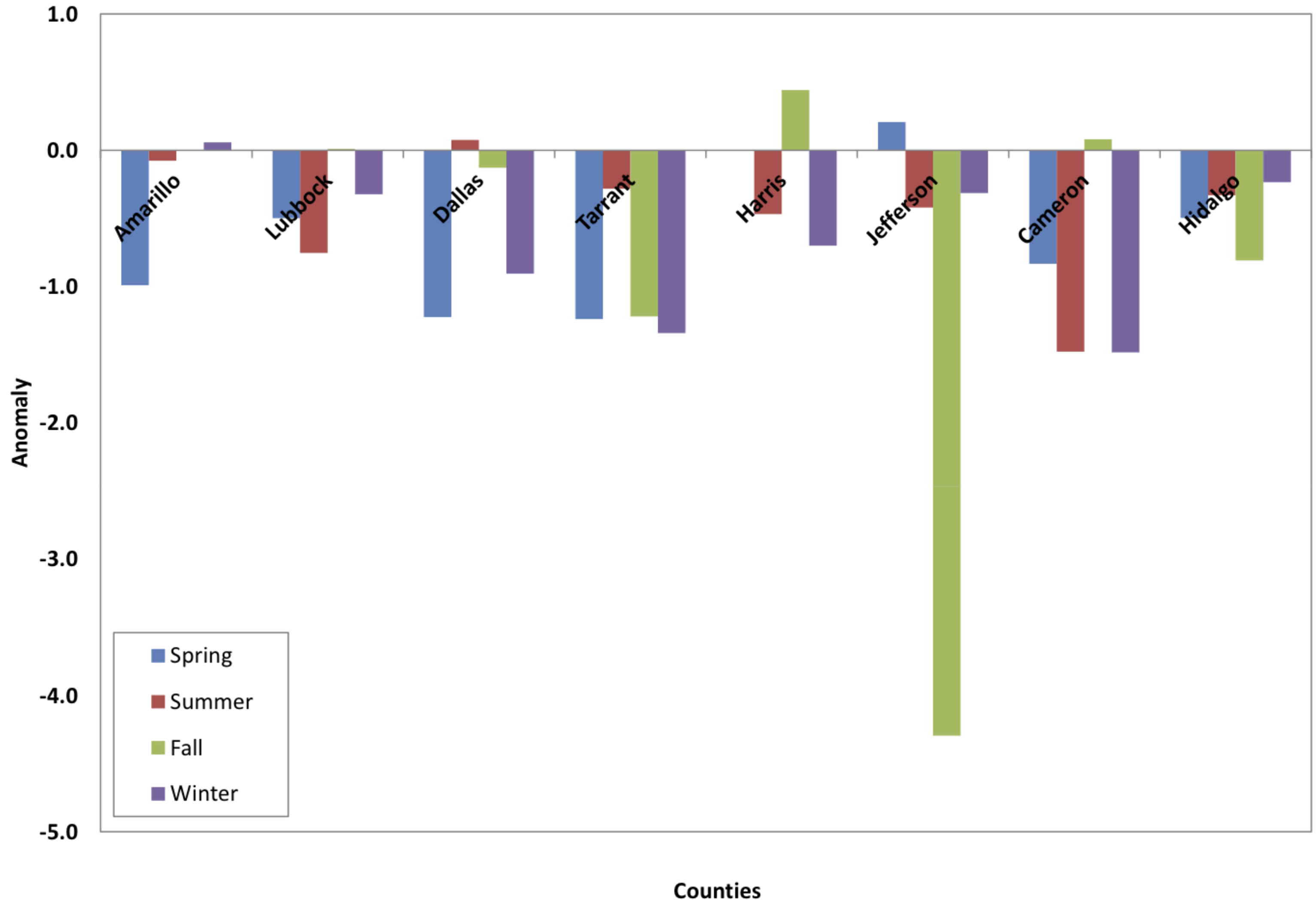


Figure A.4: Precipitation anomalies during La Niña years for study area counties.

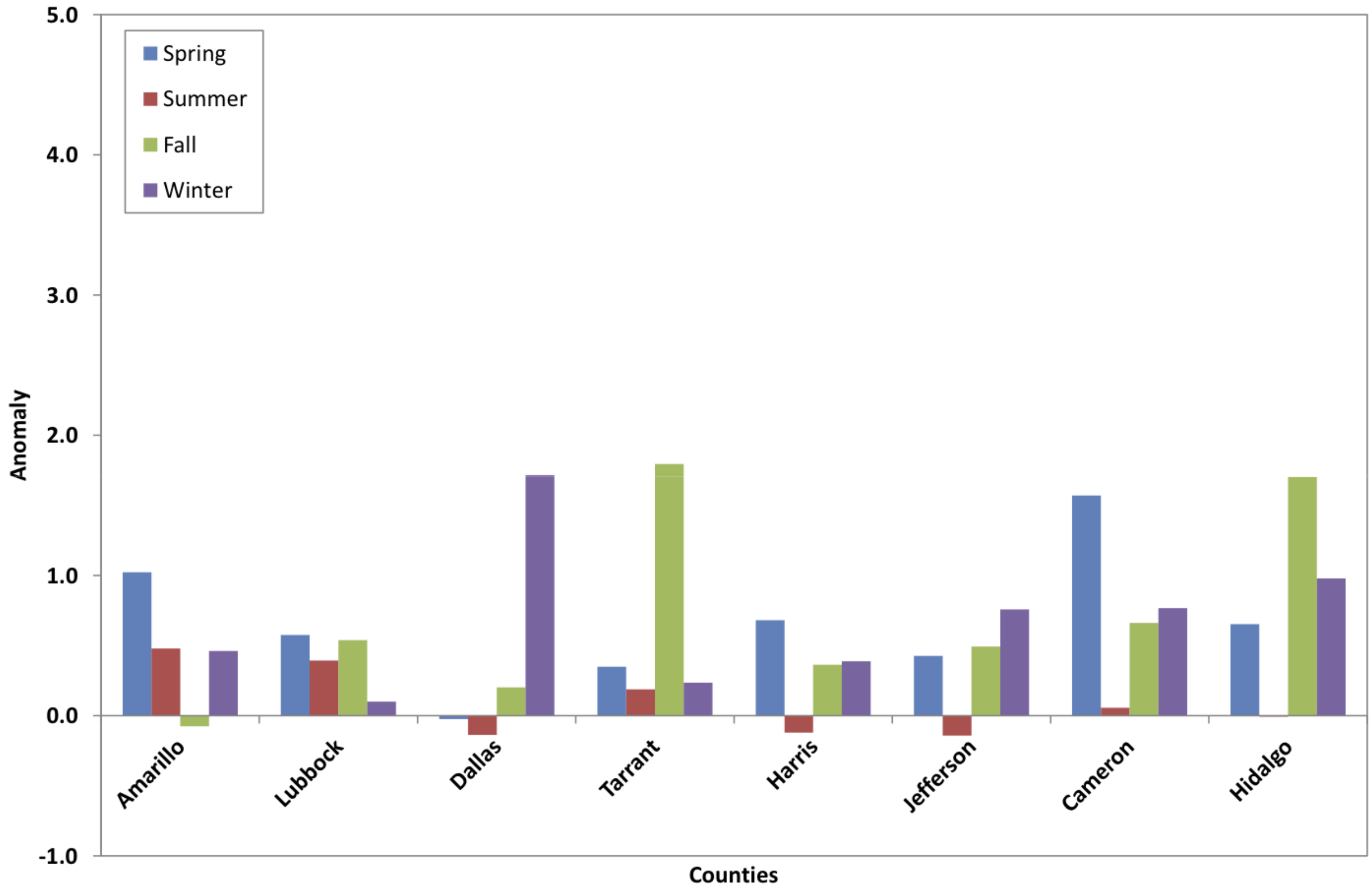


Figure A.5: Maximum temperature anomalies during La Niña years for study area counties.

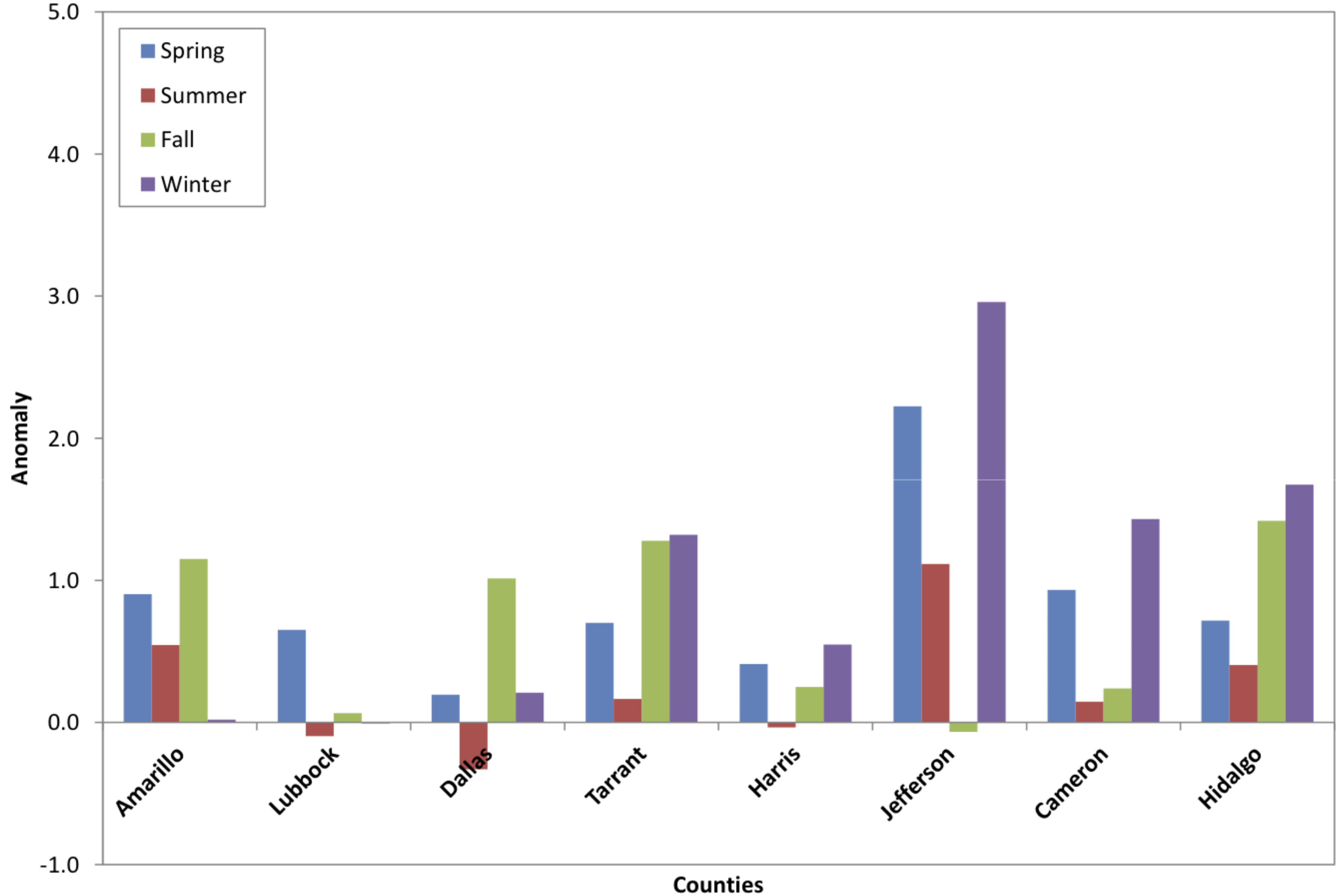


Figure A.6: Minimum temperature anomalies during La Niña years for study area counties.

B. Jet Latitude Index Results

Analysis of the Jet Latitude Index was a prime discriminator used to determine which of the GCM candidates should be selected for modeling projections of Texas climate change. The process and typical results are presented in Section 5.1.1. Additional comparisons are included in this appendix. It should be noted that the jet stream pattern for study area 2 is different from the jet stream pattern for the remaining study areas. This is because the polar jet stream curves in the region covered by study area 2, and the path traversed by the wind currents undergoes a change.

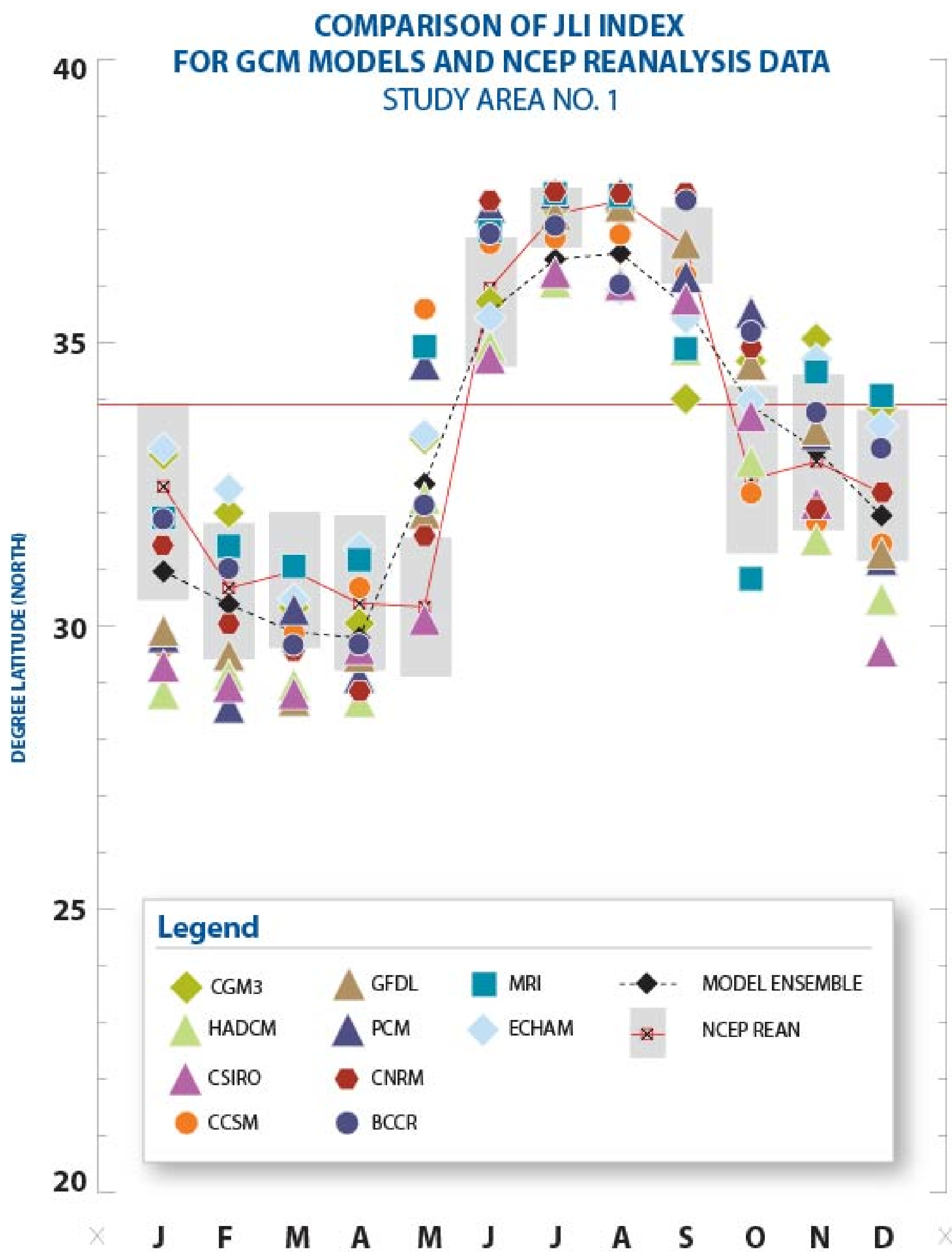


Figure B.1: Comparison of Study Area 1 JLI from GCM output and NCEP reanalysis.

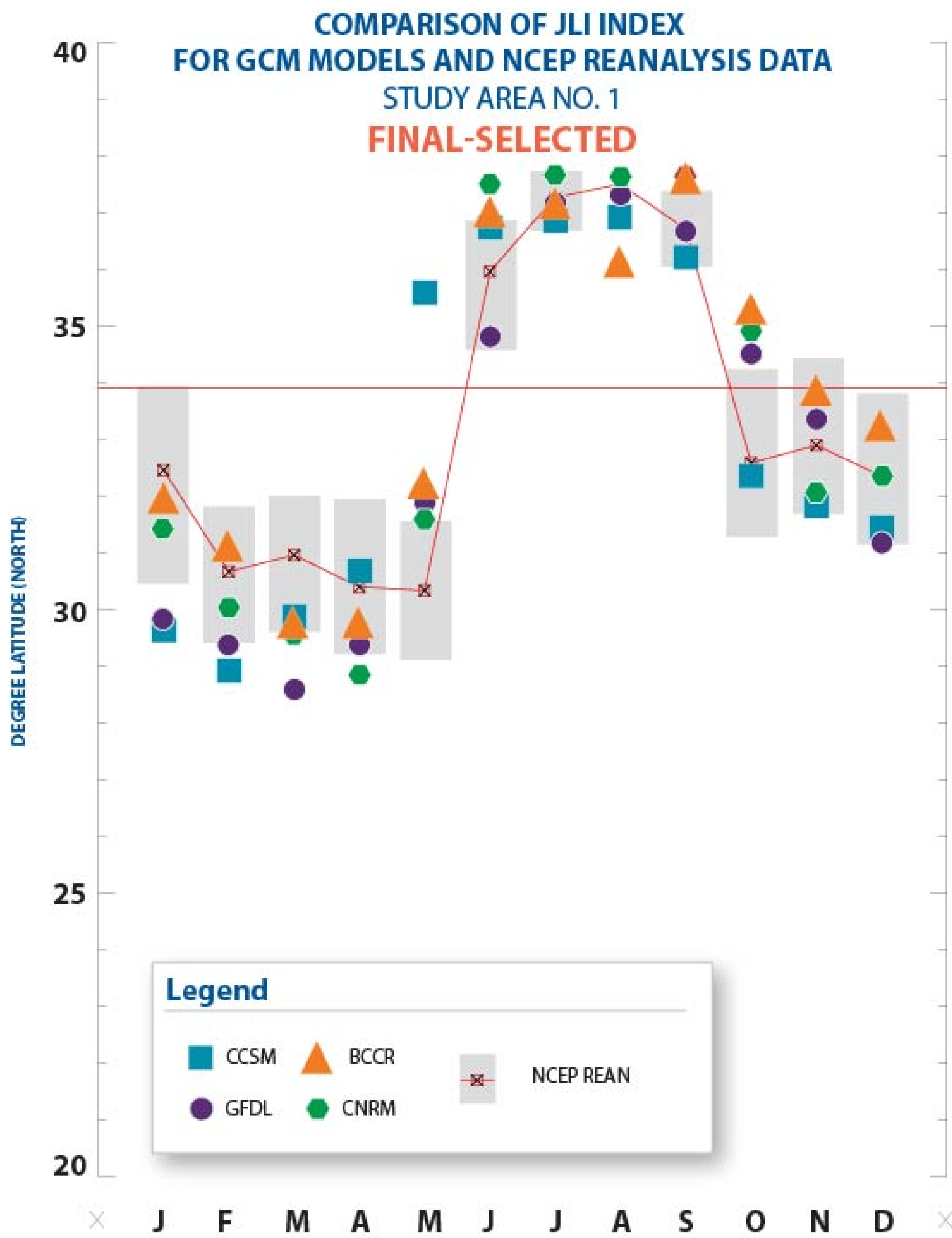


Figure B.2: Comparison of Study Area 1 JLI from selected GCM output and NCEP reanalysis.

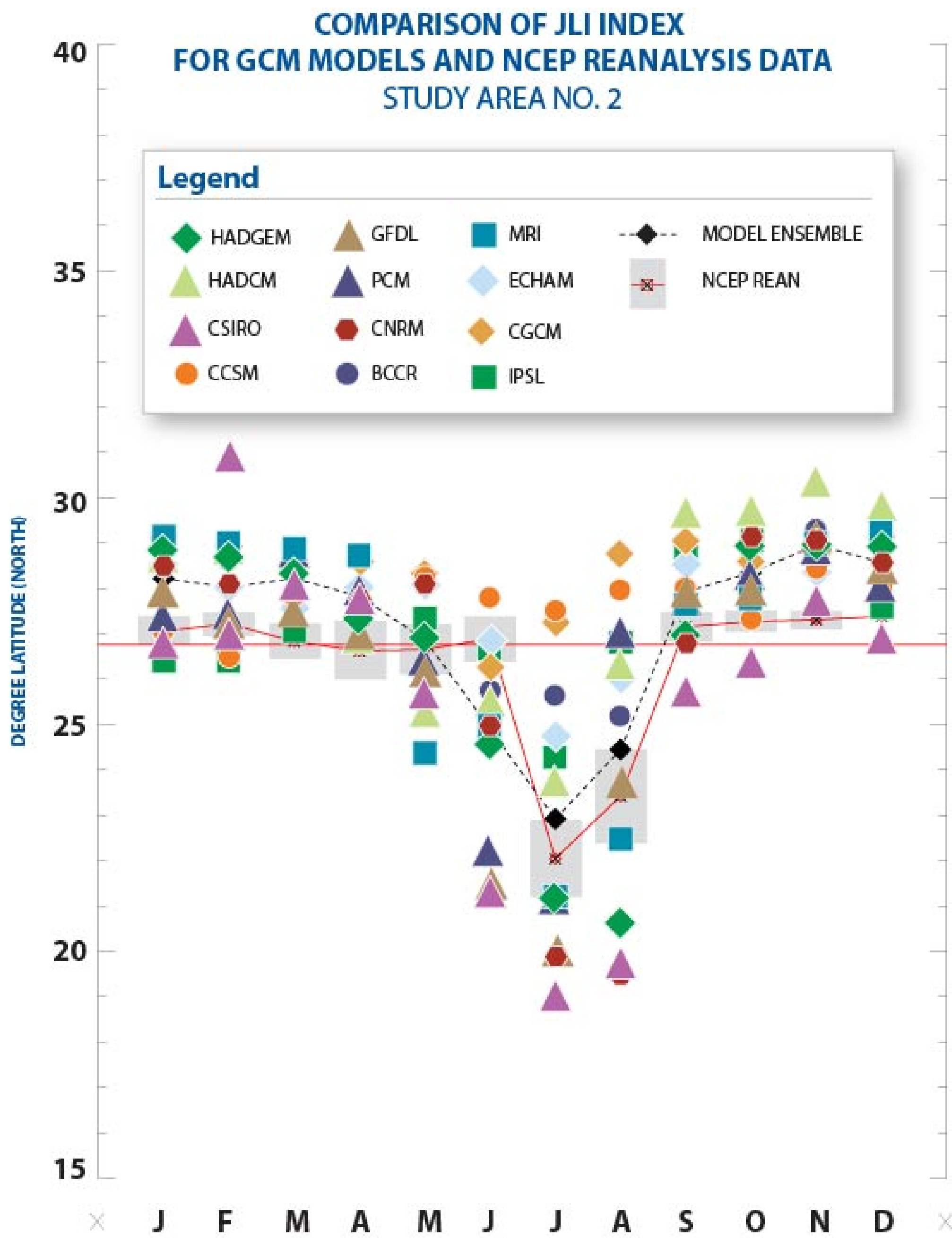


Figure B.3: Comparison of Study Area 2 JLI from GCM output and NCEP reanalysis.

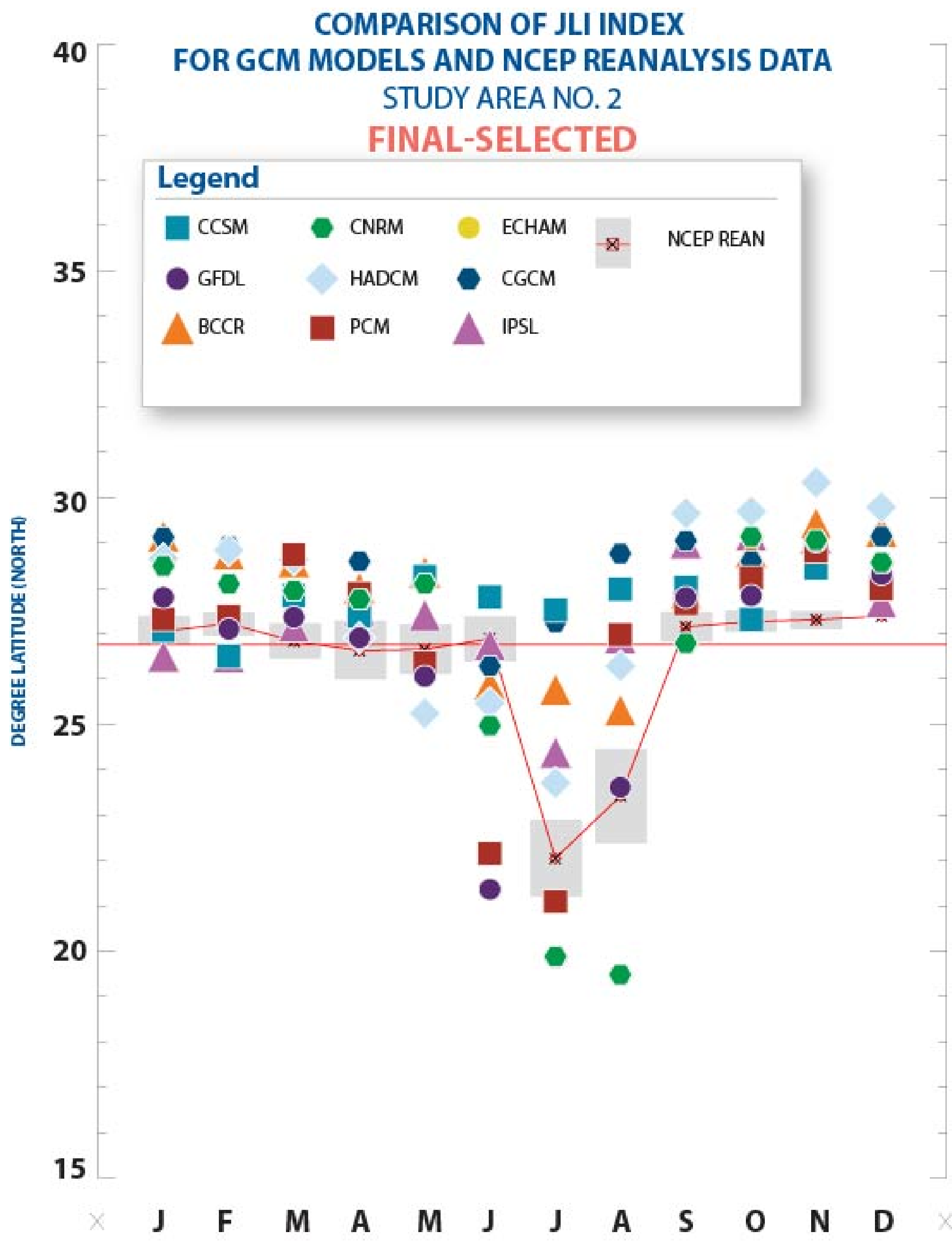


Figure B.4: Comparison of Study Area 2 JLI from selected GCM output and NCEP reanalysis.

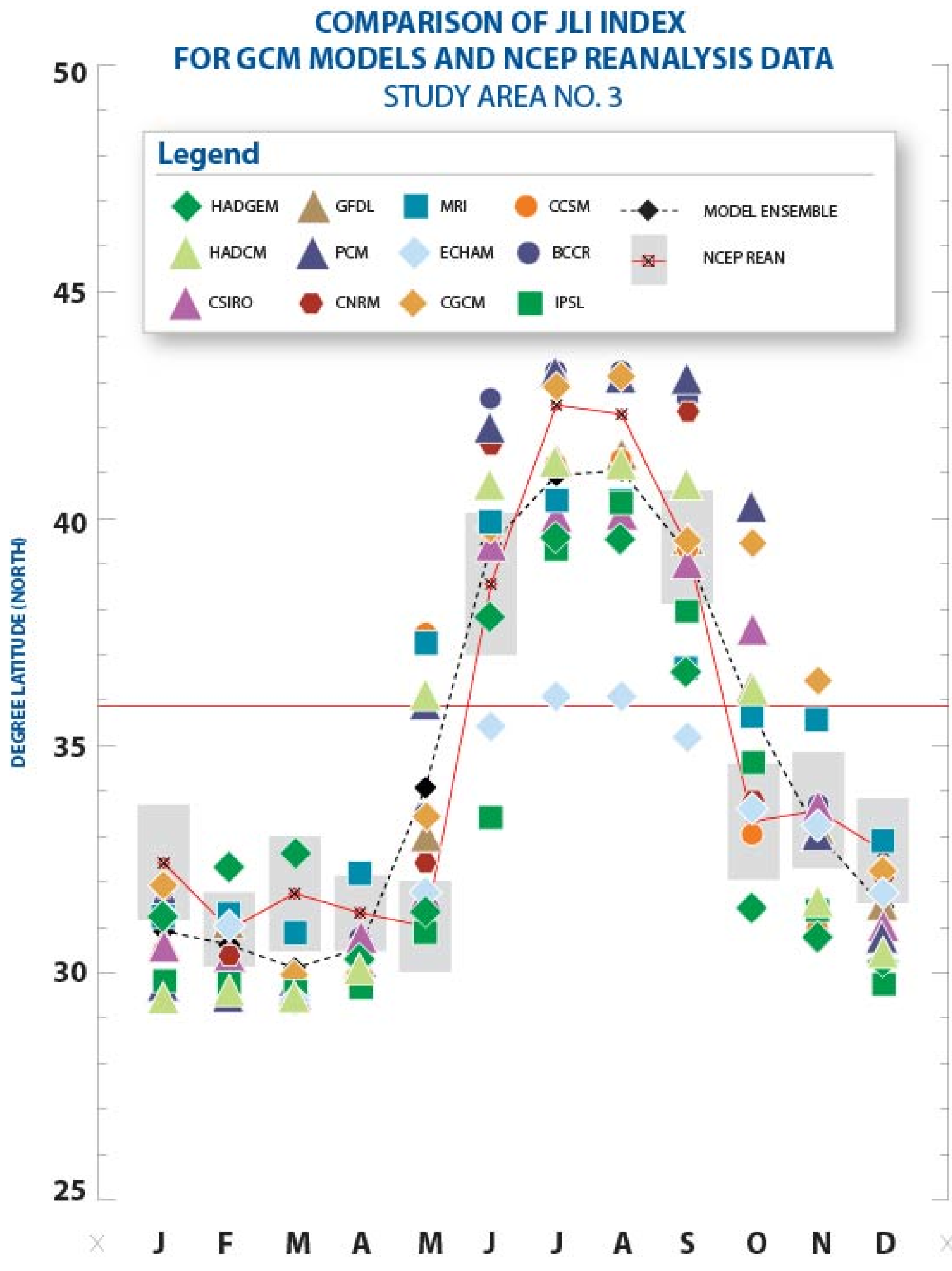


Figure B.5: Comparison of Study Area 3 JLI from GCM output and NCEP reanalysis.

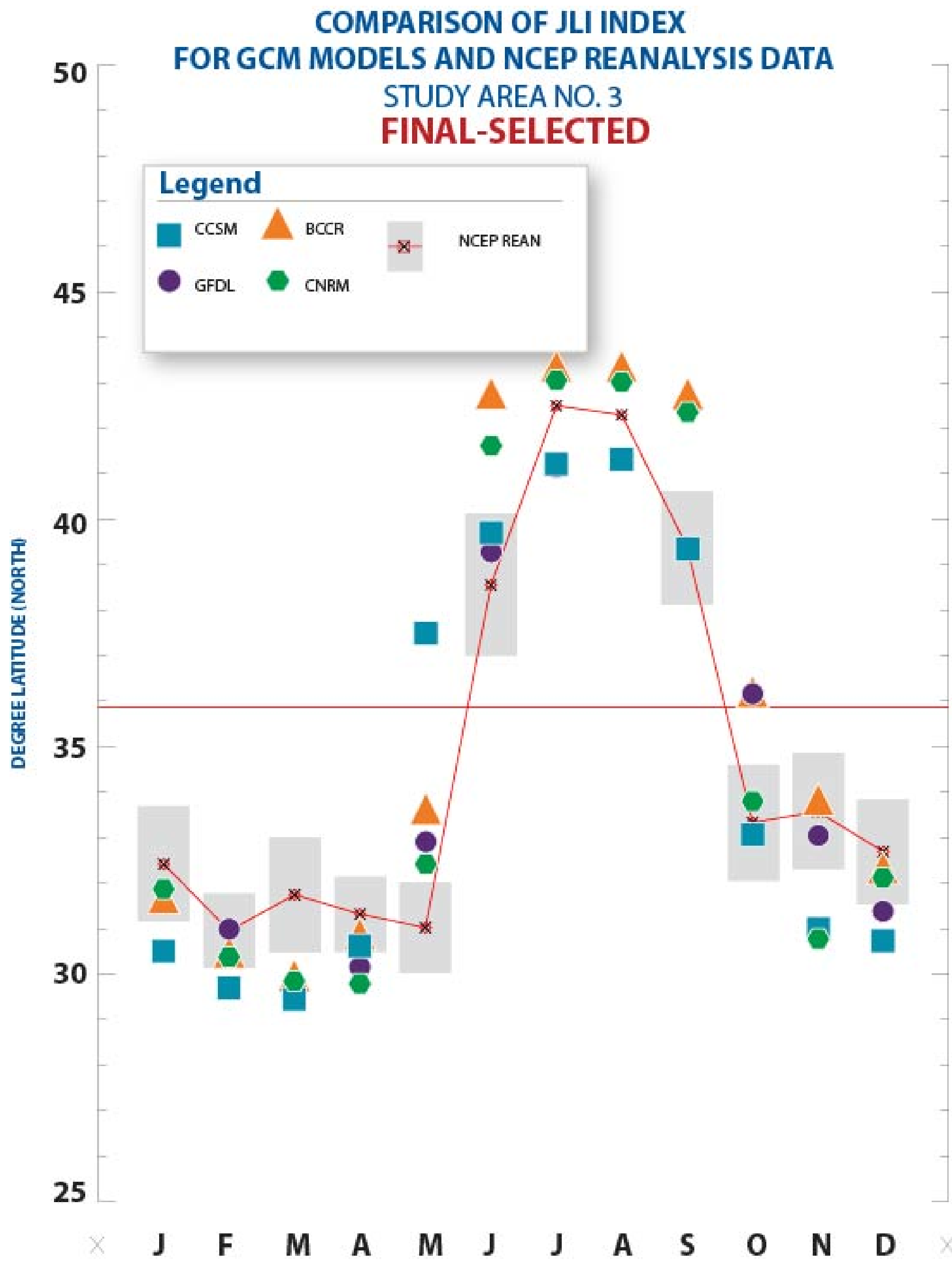


Figure B.6: Comparison of Study Area 3 JLI from selected GCM output and NCEP reanalysis.

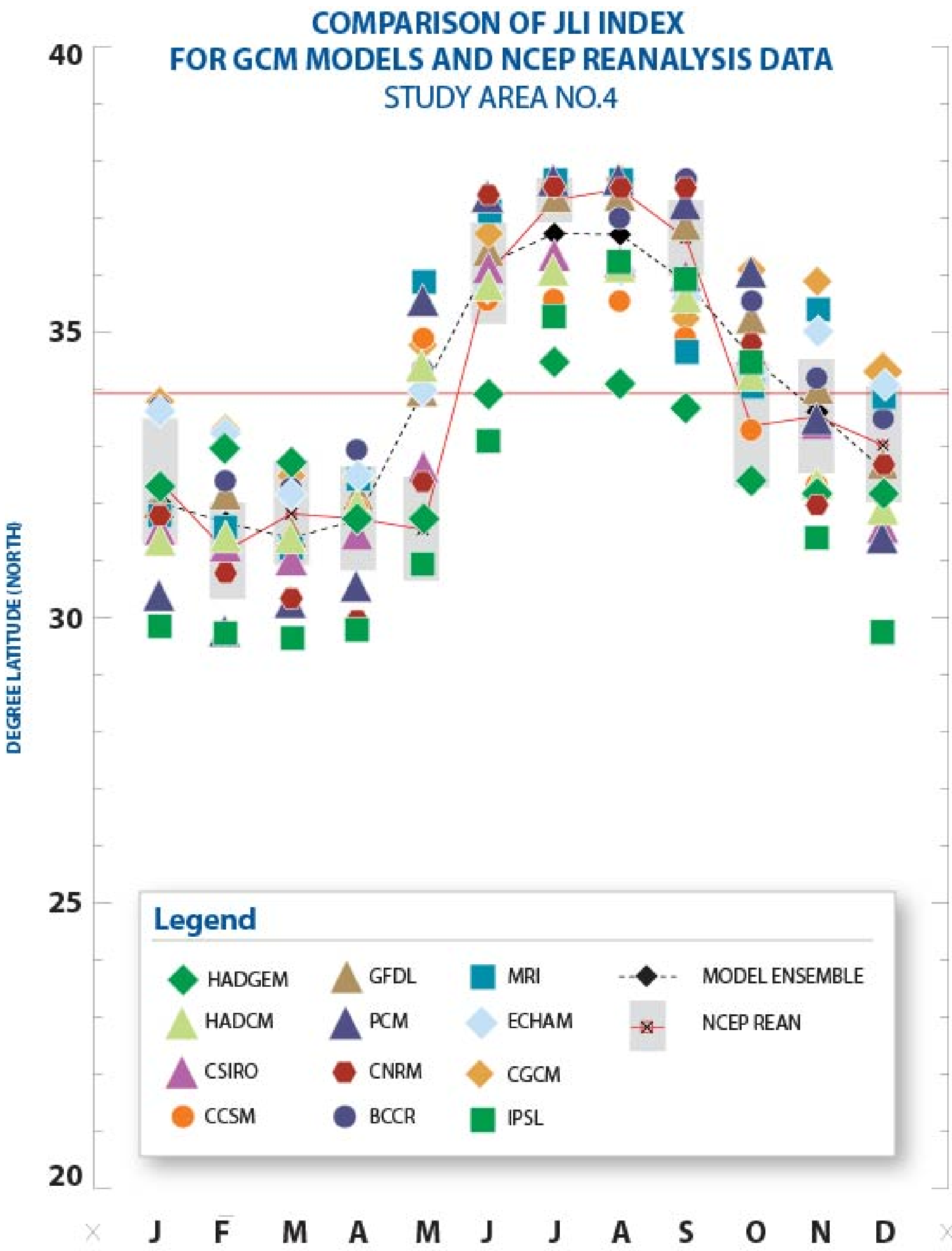


Figure B.7: Comparison of Study Area 4 JLI from GCM output and NCEP reanalysis.

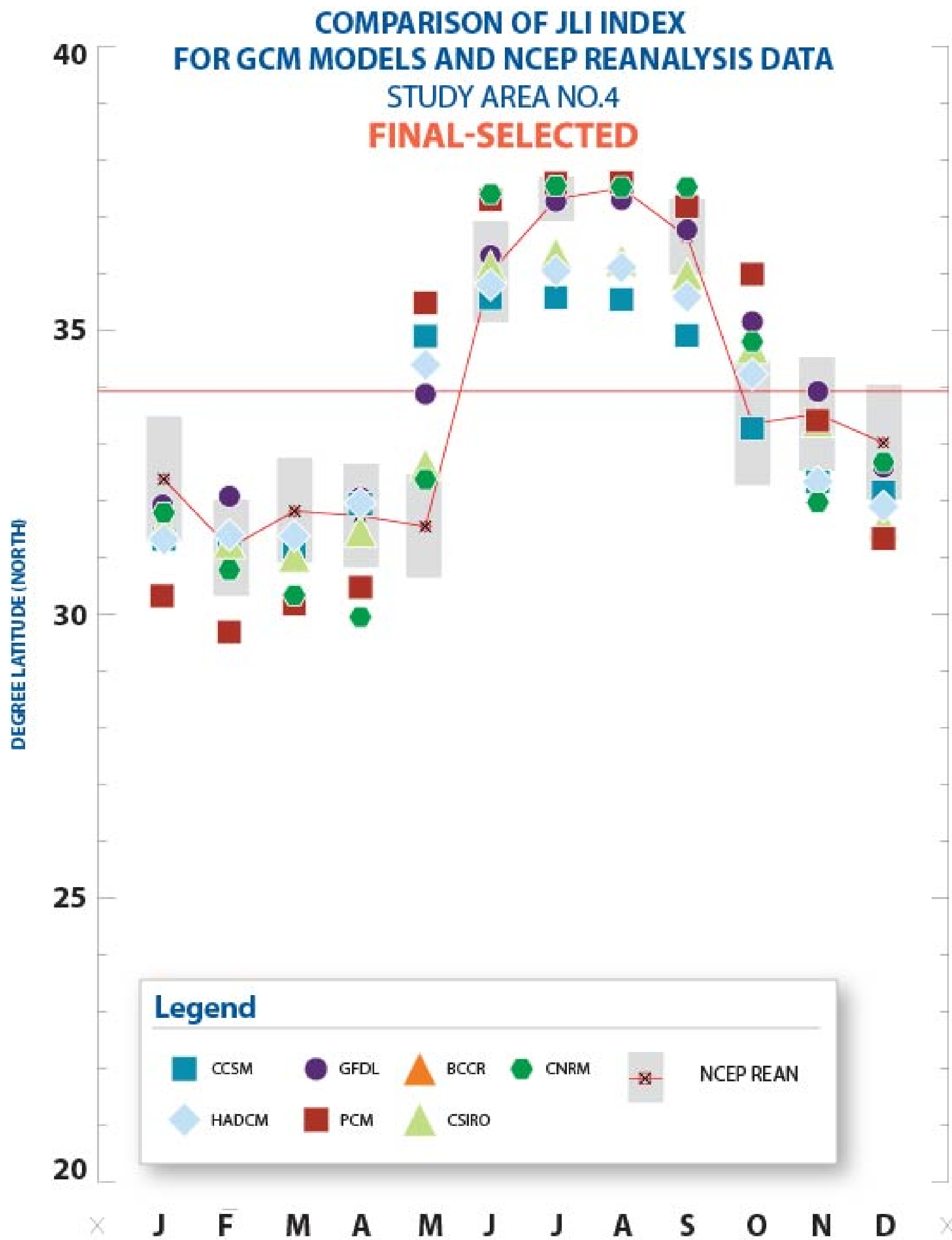


Figure B.8: Comparison of Study Area 4 JLI from selected GCM output and NCEP reanalysis.

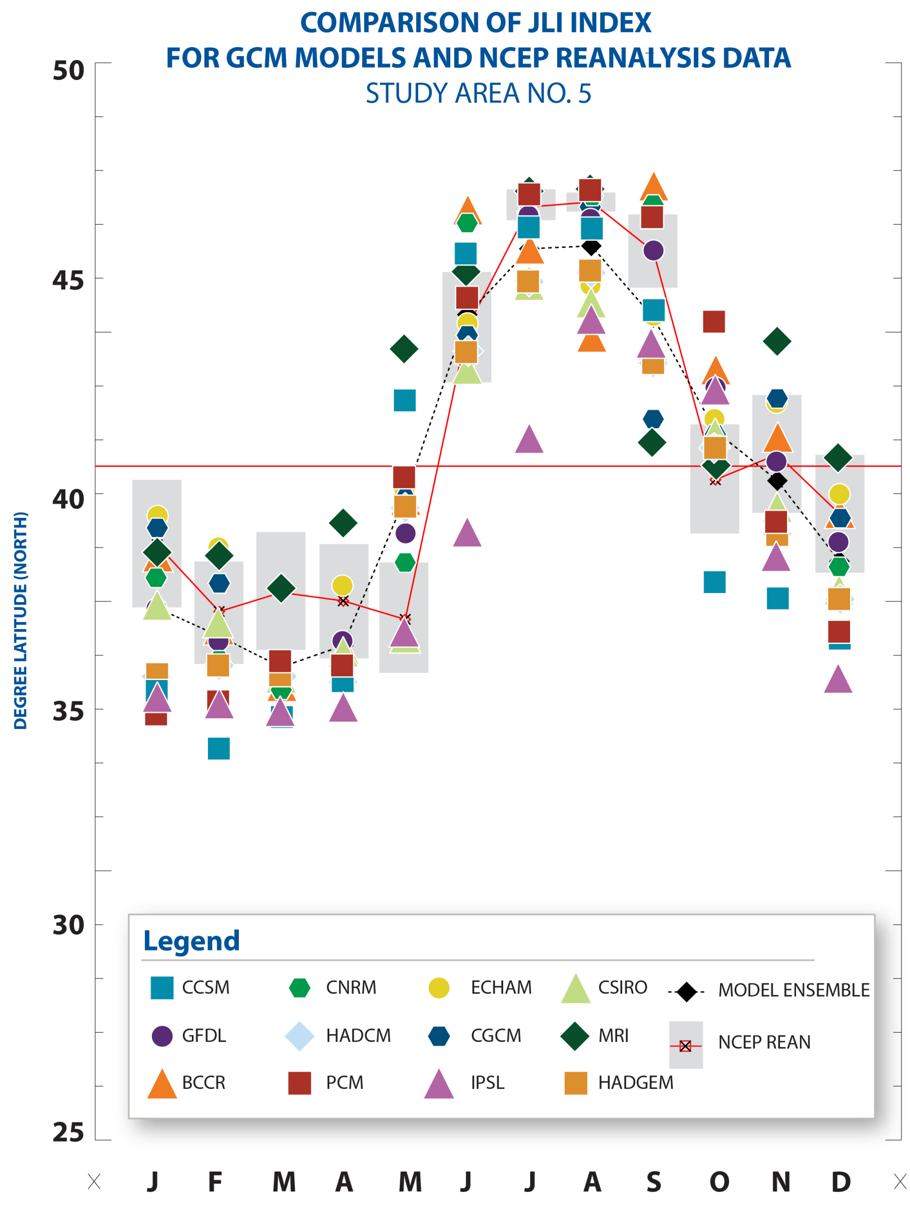


Figure B.9: Comparison of Study Area 5 JLI from GCM output and NCEP reanalysis.

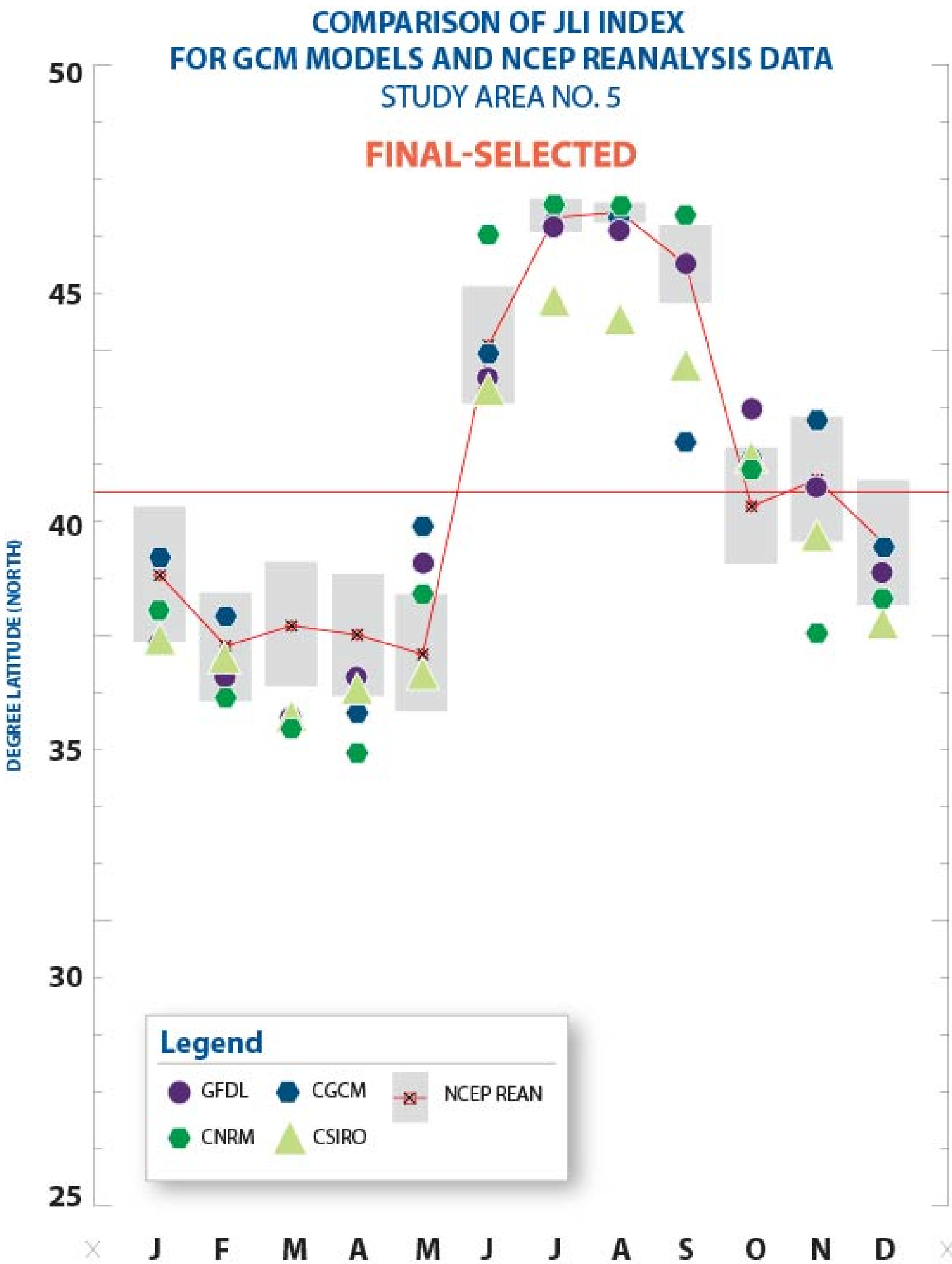


Figure B.10: Comparison of Study Area 5 JLI from selected GCM output and NCEP reanalysis.

C. GCM Convergence Results

In the context of GCM output, convergence refers to the tendency (or lack thereof) of GCMs to produce results that are similar in some gross sense. That is, if GCMs are convergent, then their projections of climate change are similar. The evaluation of convergence of the selected GCMs is discussed in Section 5.3 and typical results are presented to support the analysis and conclusions of that portion of the report. The remaining figures are included in this appendix.

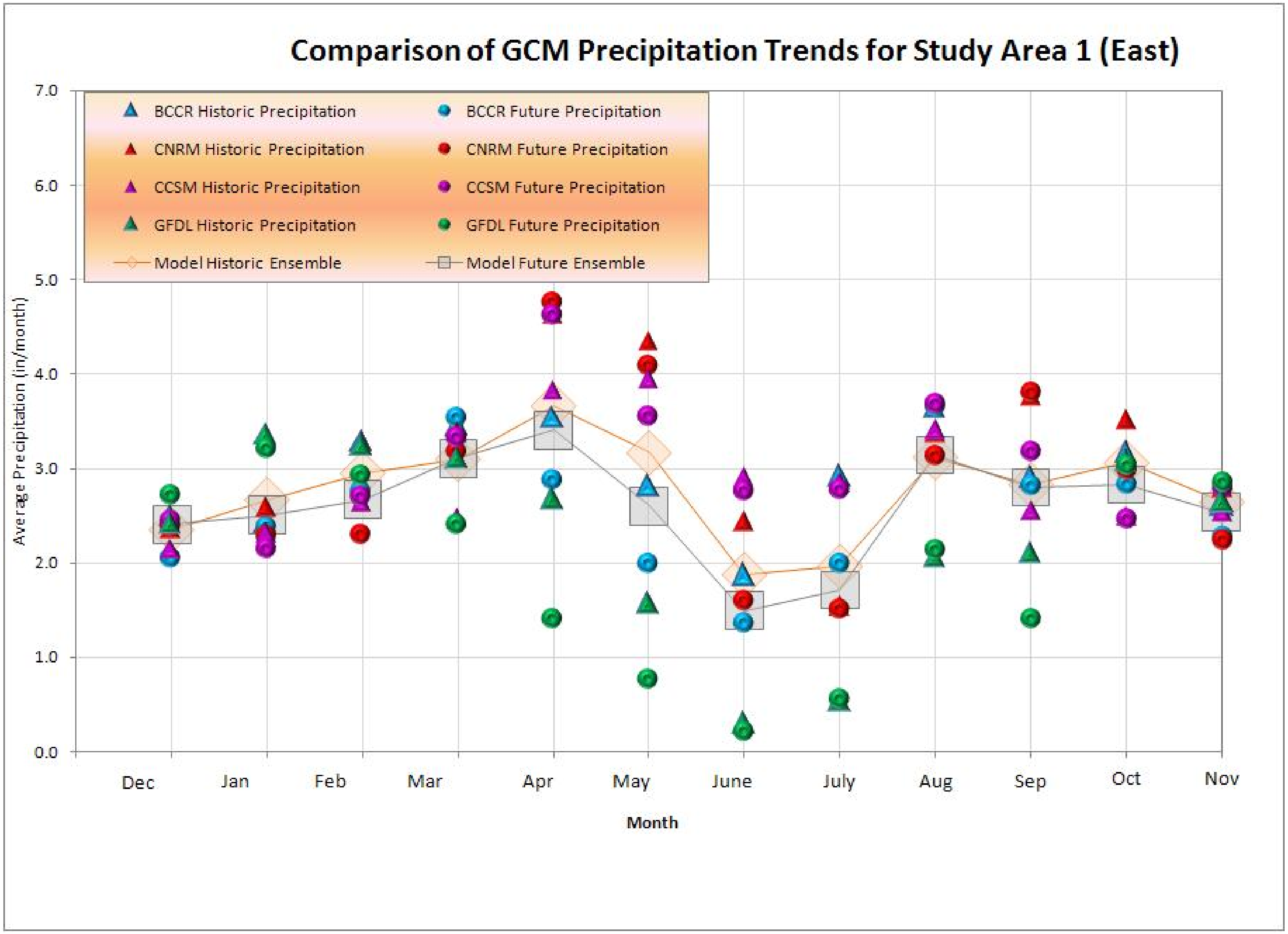


Figure C.1: Comparison of GCM precipitation trends for Study Area 1 (East).

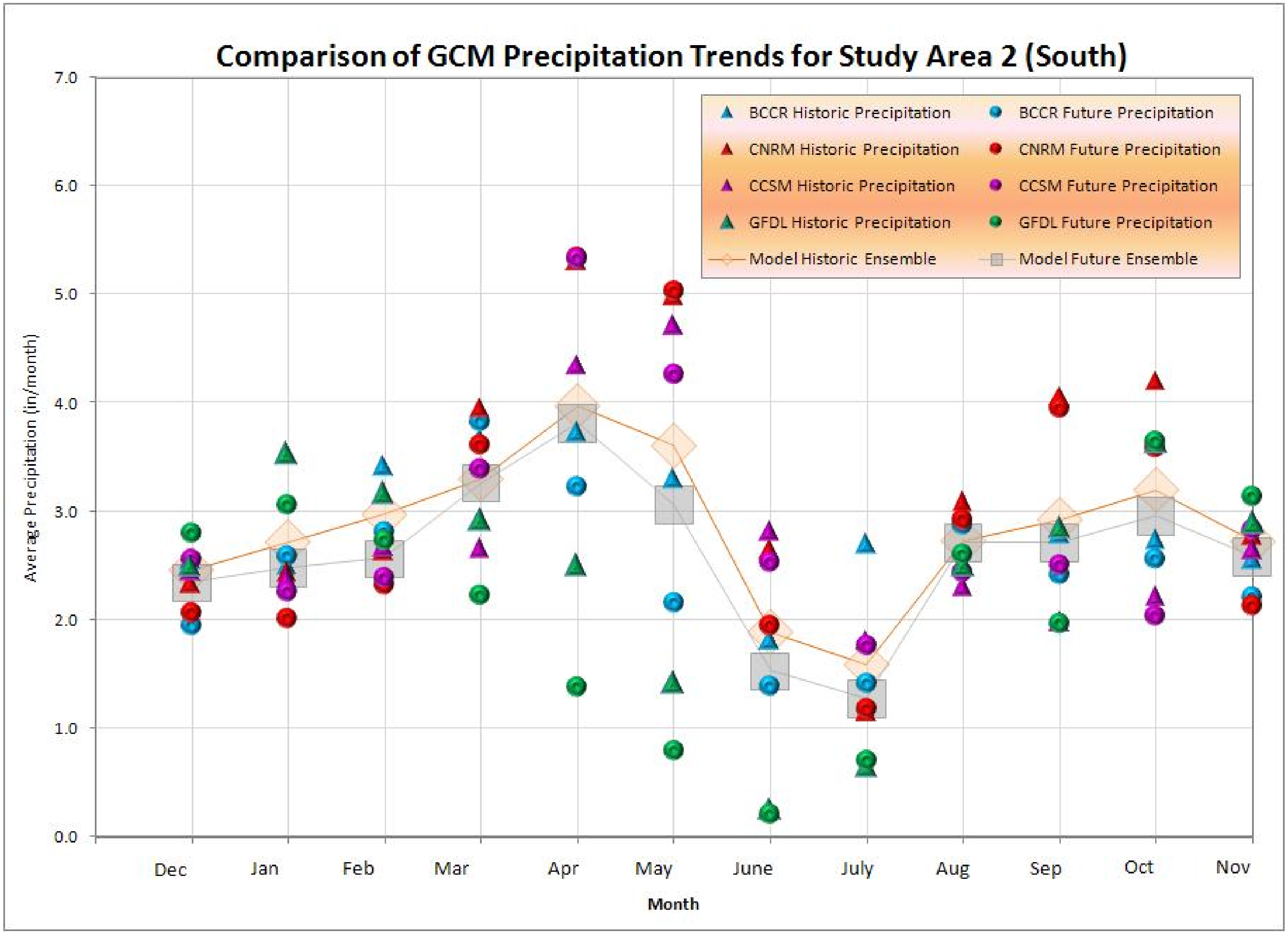


Figure C.2: Comparison of GCM precipitation trends for Study Area 2 (South).

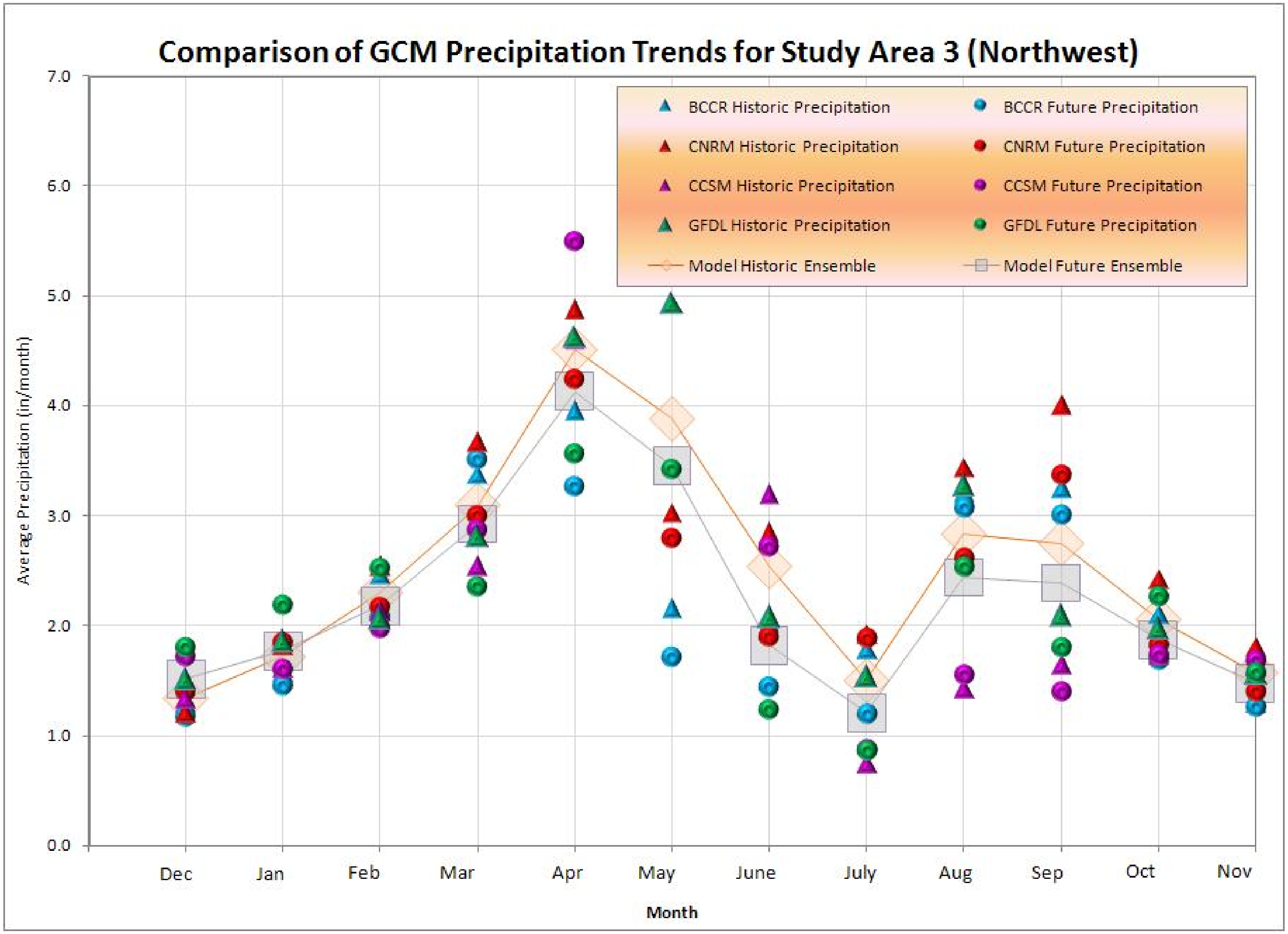


Figure C.3: Comparison of GCM precipitation trends for Study Area 3 (Northwest).

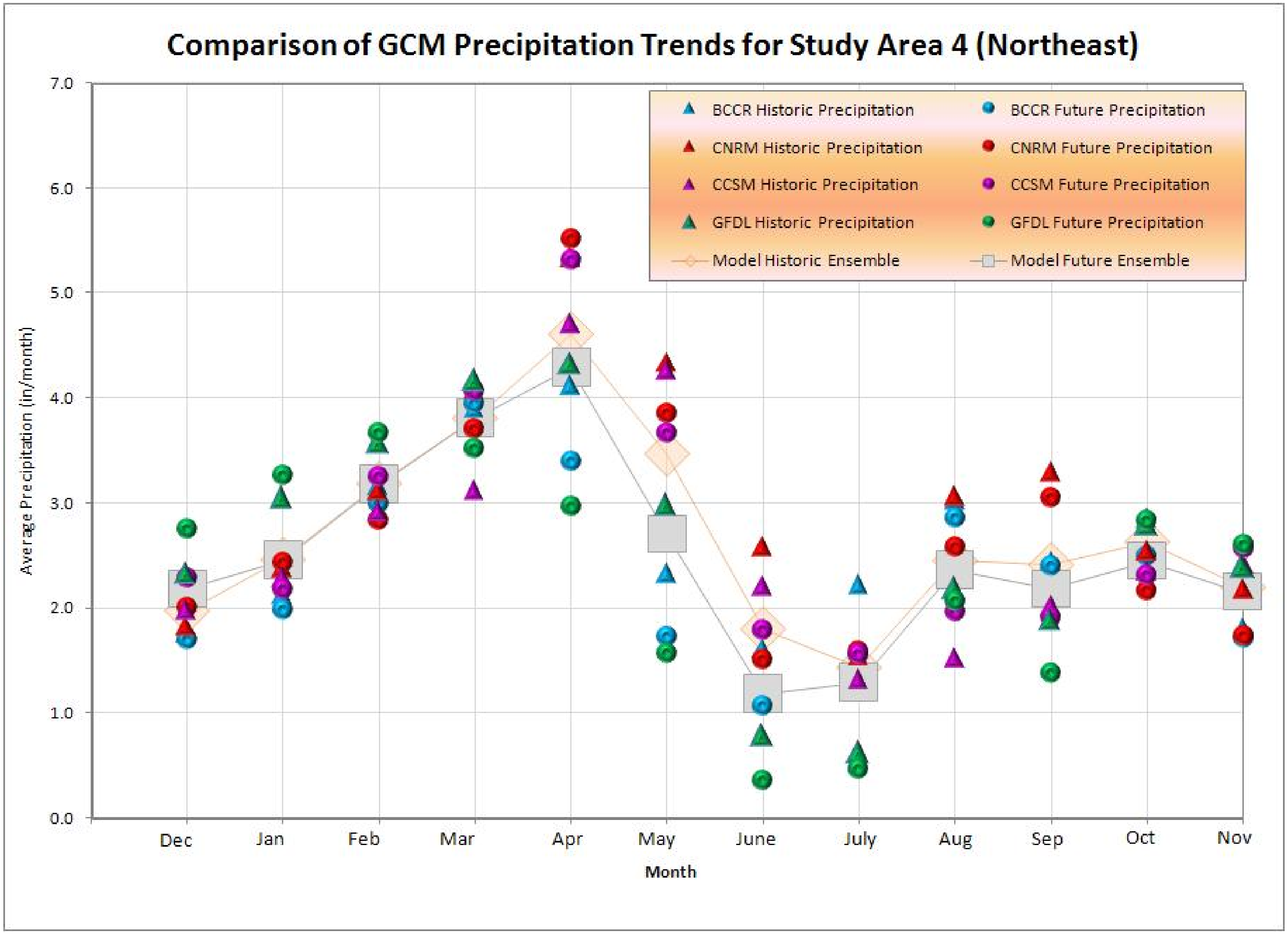


Figure C.4: Comparison of GCM precipitation trends for Study Area 4 (Northeast).

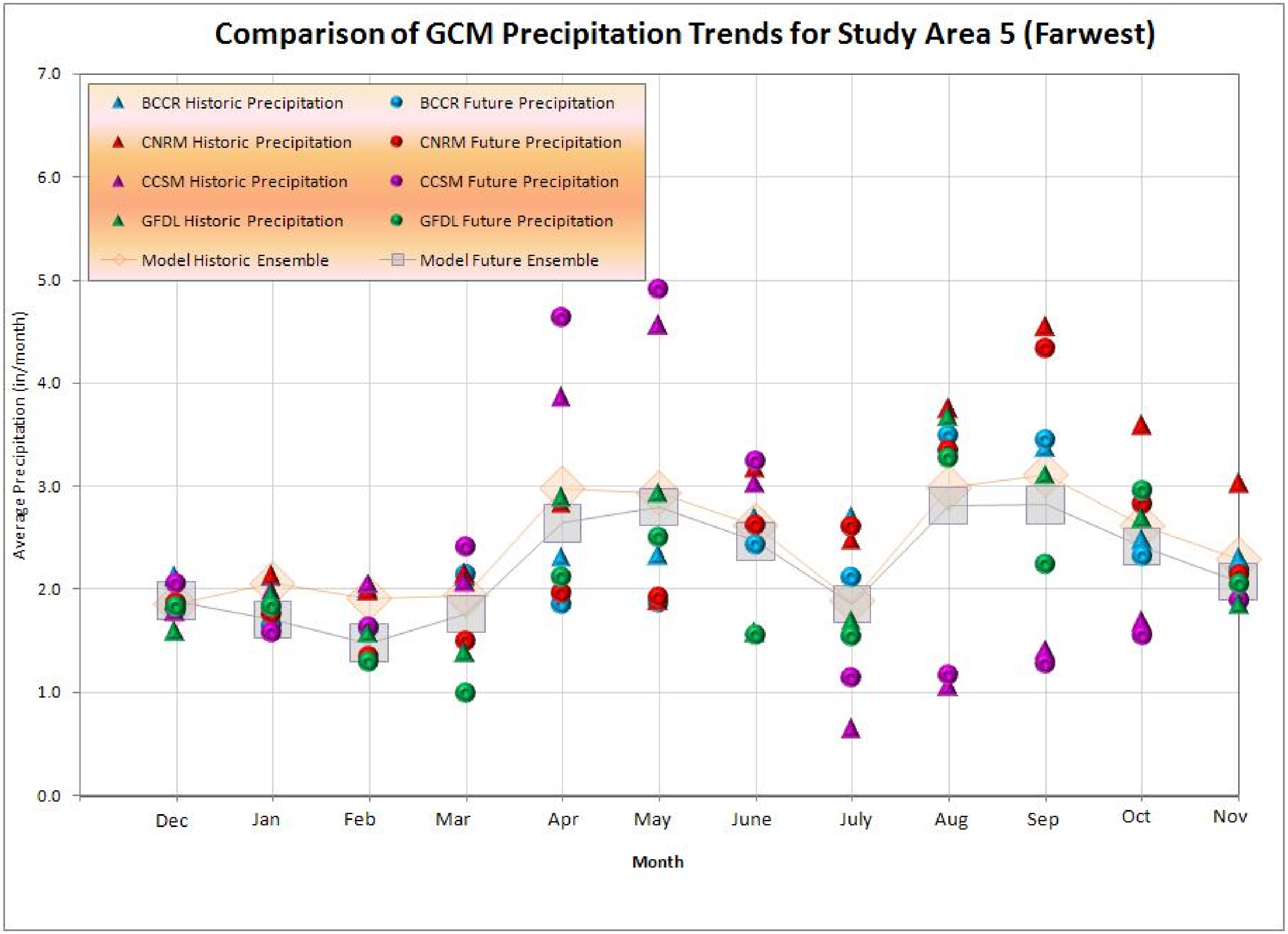


Figure C.5: Comparison of GCM precipitation trends for Study Area 5 (Far West).

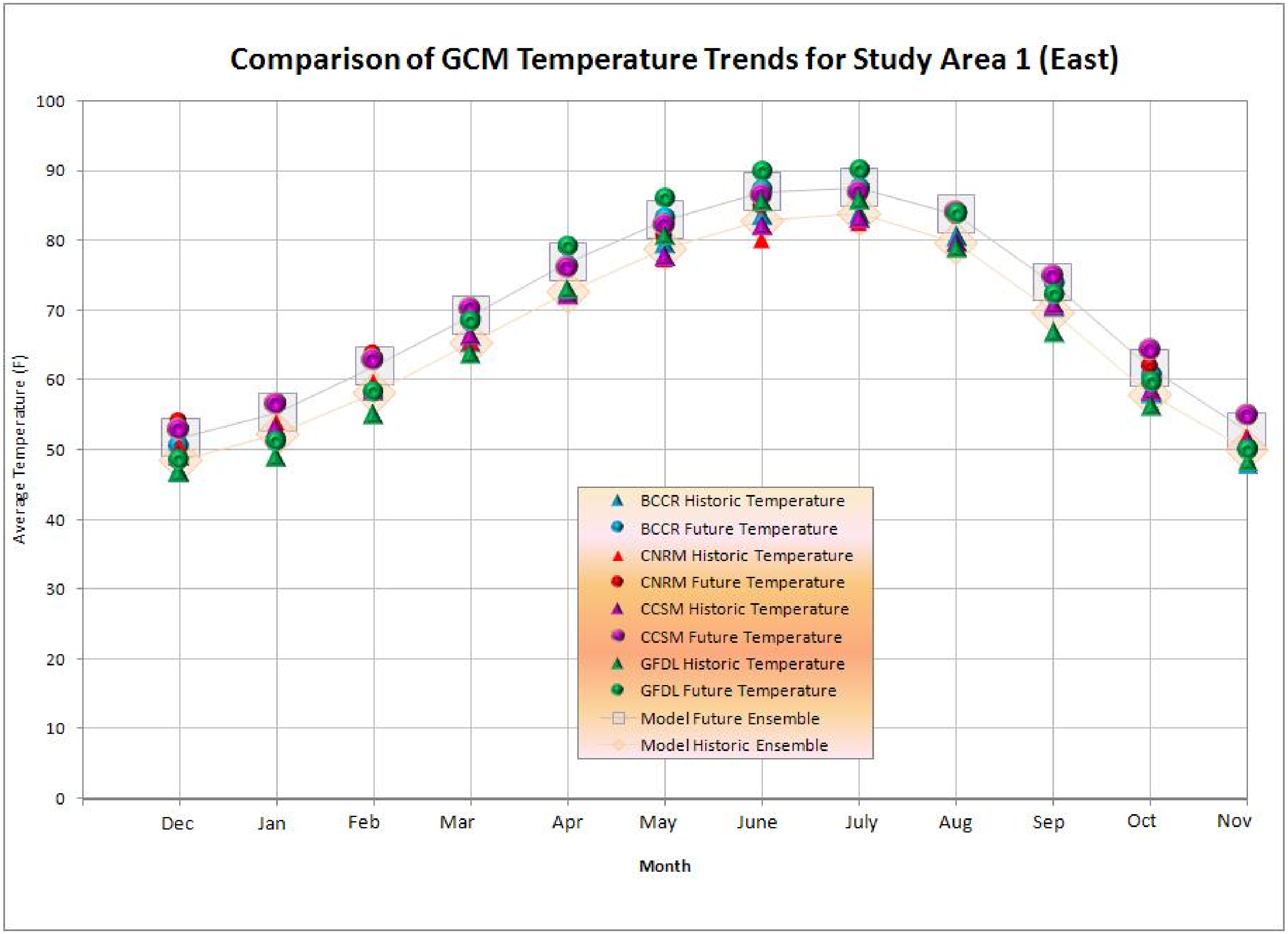


Figure C.6: Comparison of GCM temperature trends for Study Area 1 (East).

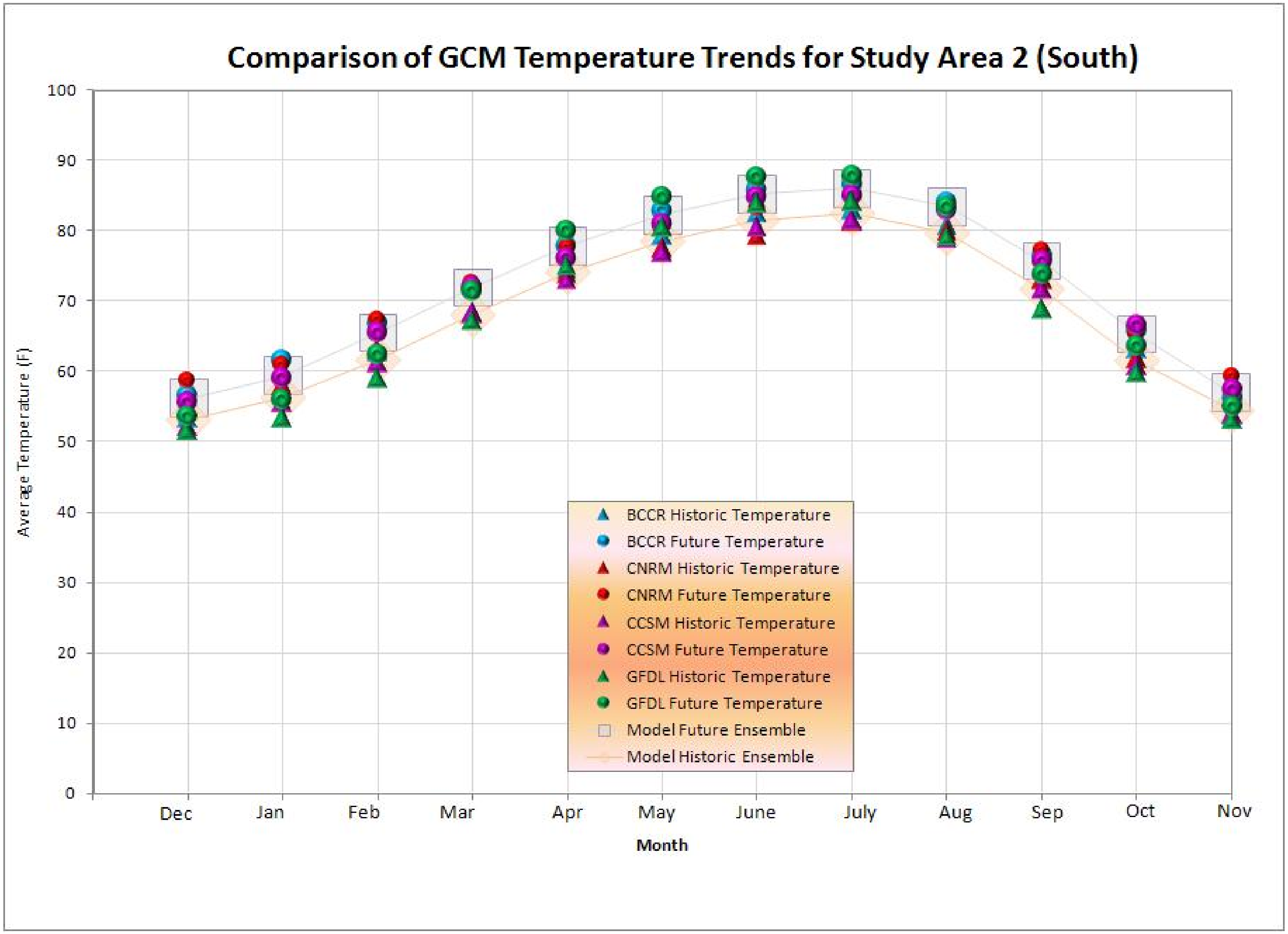


Figure C.7: Comparison of GCM temperature trends for Study Area 2 (South).

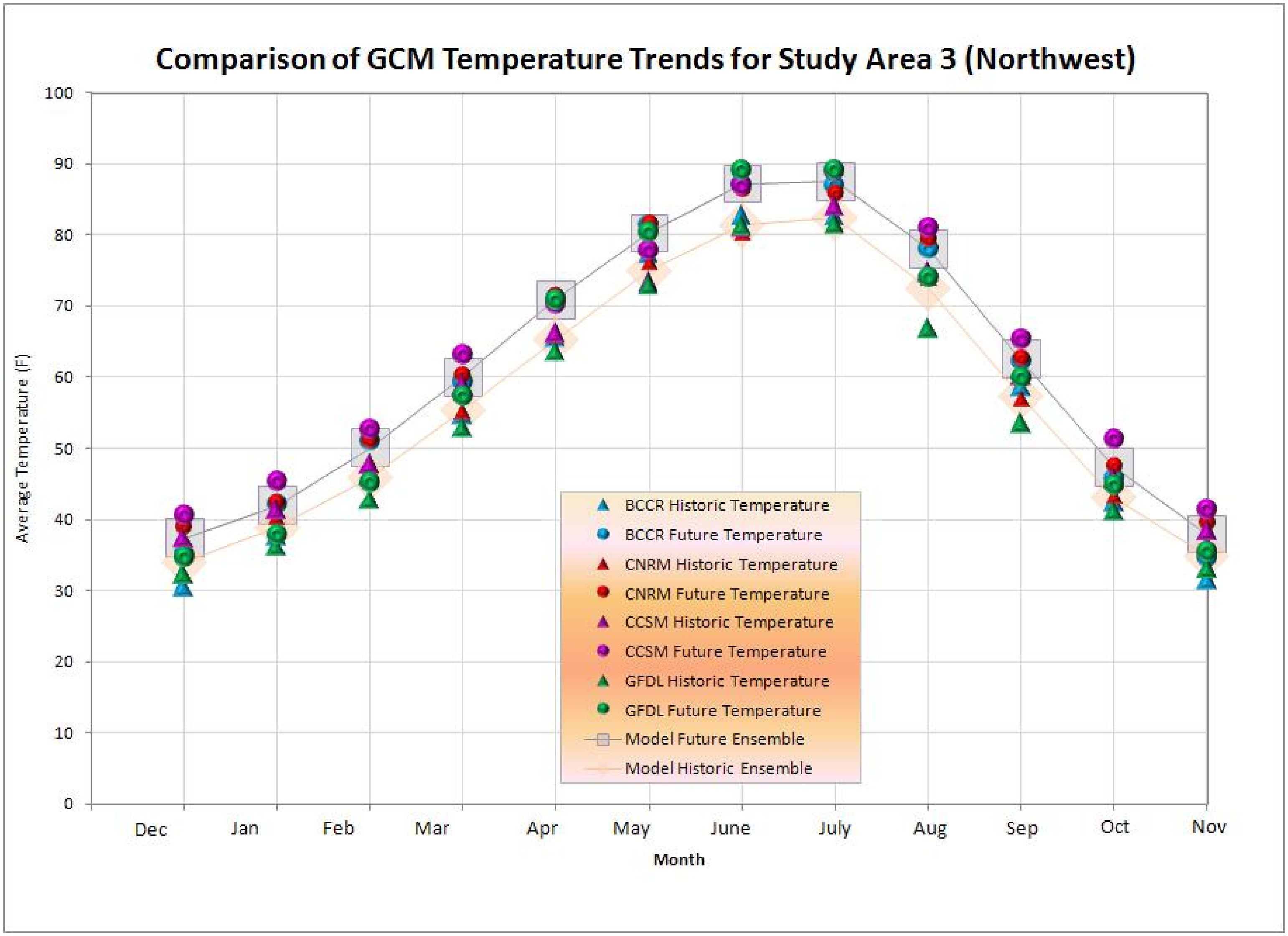


Figure C.8: Comparison of GCM temperature trends for Study Area 3 (Northwest).

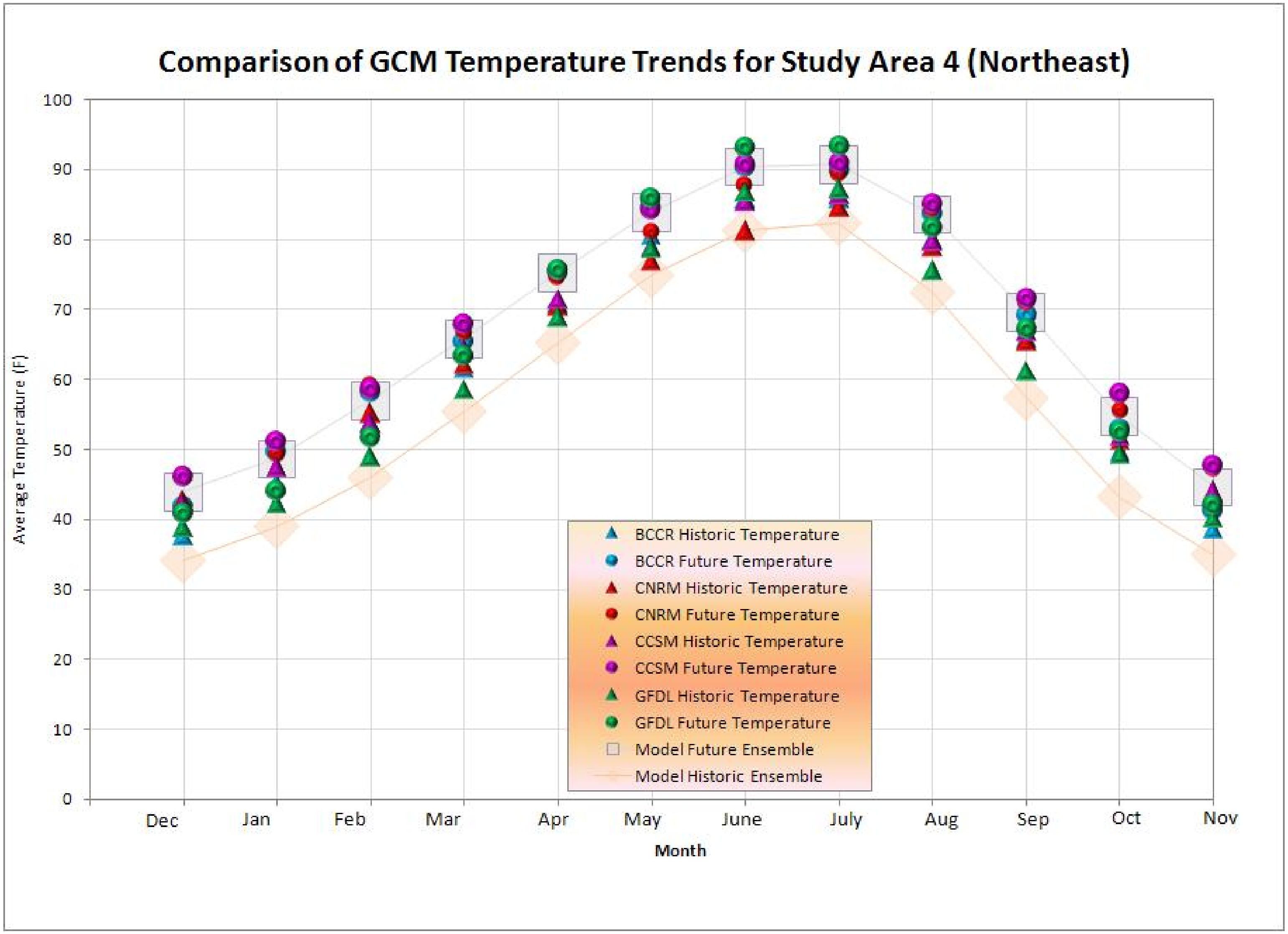


Figure C.9: Comparison of GCM temperature trends for Study Area 4 (Northeast).

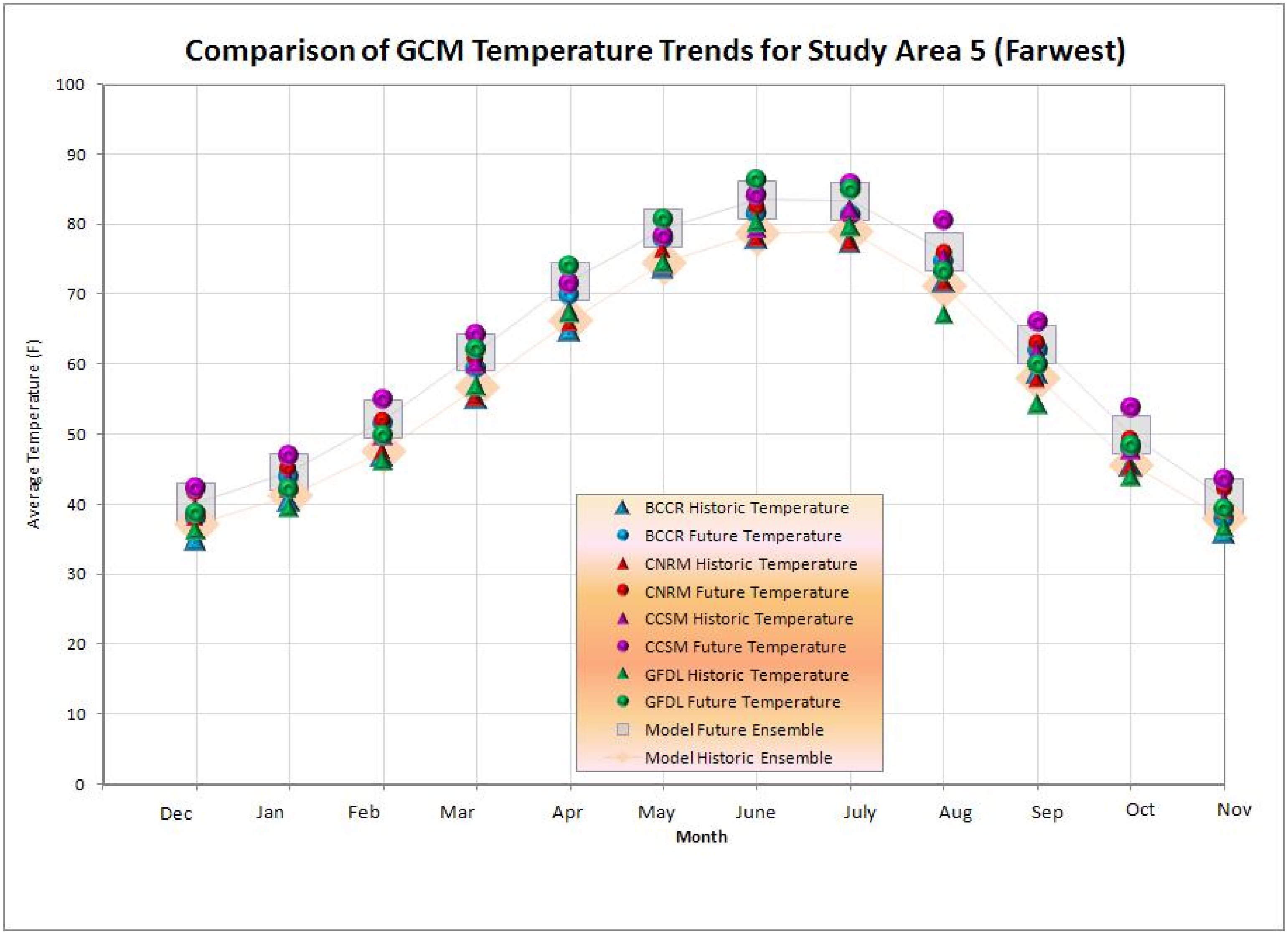


Figure C.10: Comparison of GCM temperature trends for Study Area 5 (Far West).

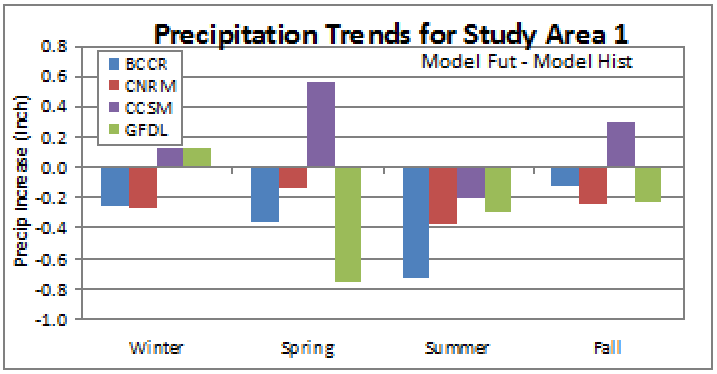


Figure C.11: Comparison of GCM precipitation trends for Study Area 1 (East).

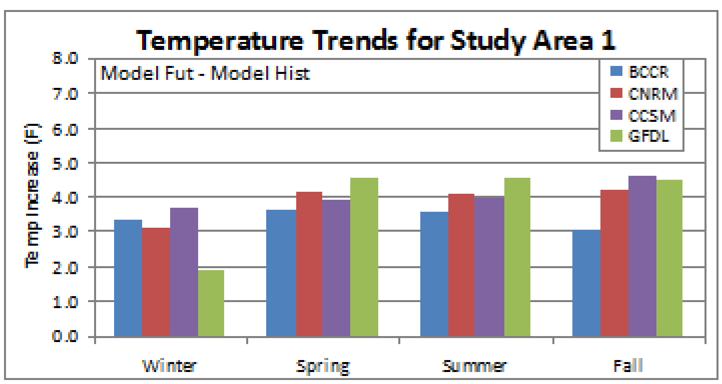


Figure C.12: Comparison of GCM temperature trends for Study Area 1 (East).

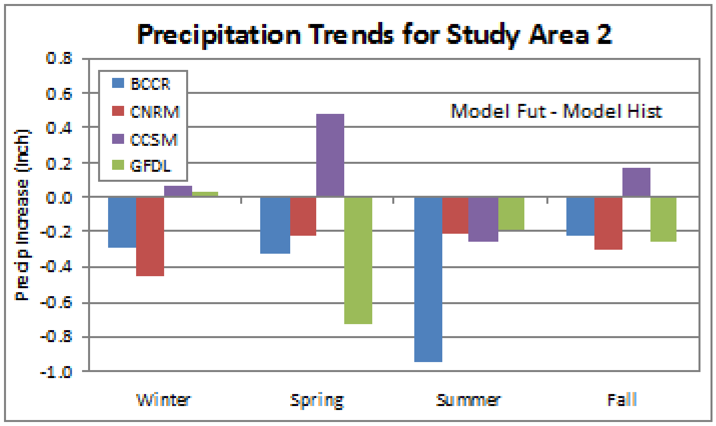


Figure C.13: Comparison of GCM precipitation trends for Study Area 2 (South).

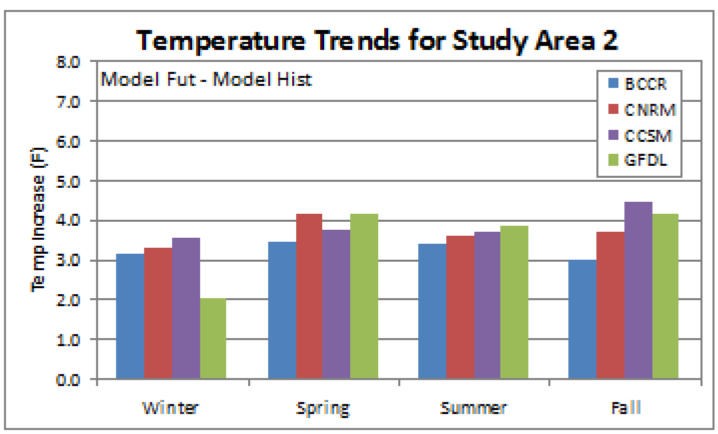


Figure C.14: Comparison of GCM precipitation trends for Study Area 2 (South).

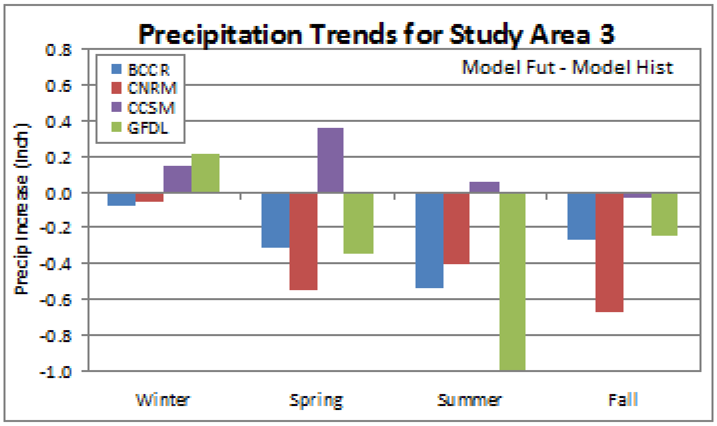


Figure C.15: Comparison of GCM precipitation trends for Study Area 3 (Northwest).

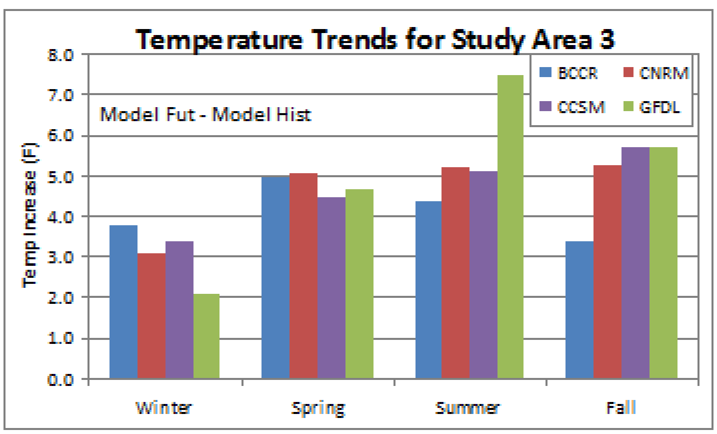


Figure C.16: Comparison of GCM precipitation trends for Study Area 3 (Northwest).

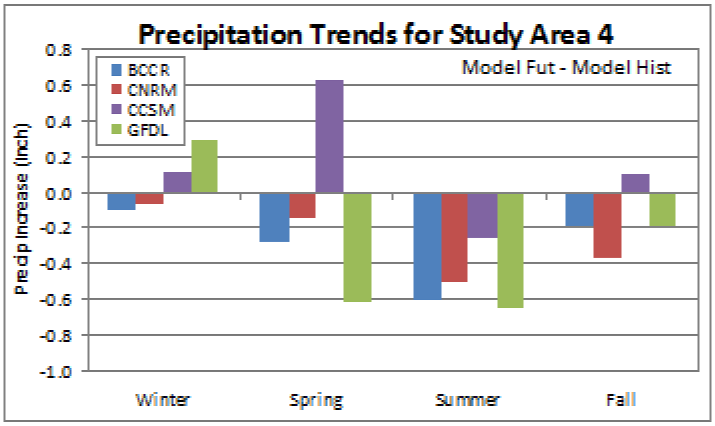


Figure C.17: Comparison of GCM precipitation trends for Study Area 4 (Northeast).

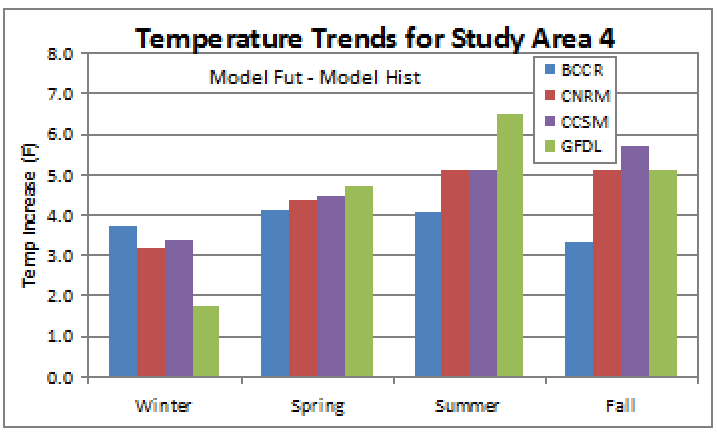


Figure C.18: Comparison of GCM precipitation trends for Study Area 4 (Northeast).

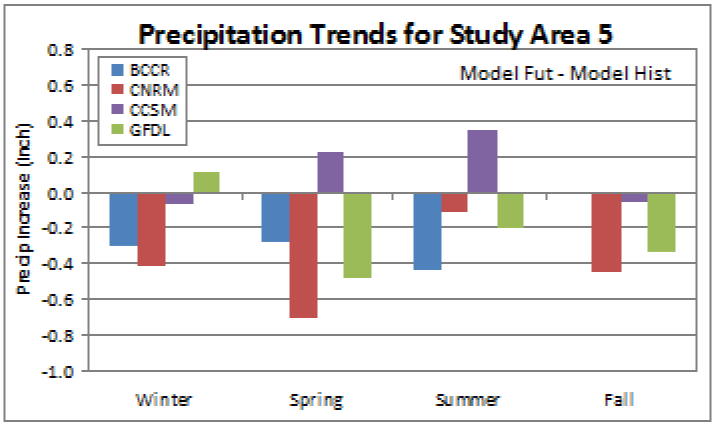


Figure C.19: Comparison of GCM precipitation trends for Study Area 5 (Far West).

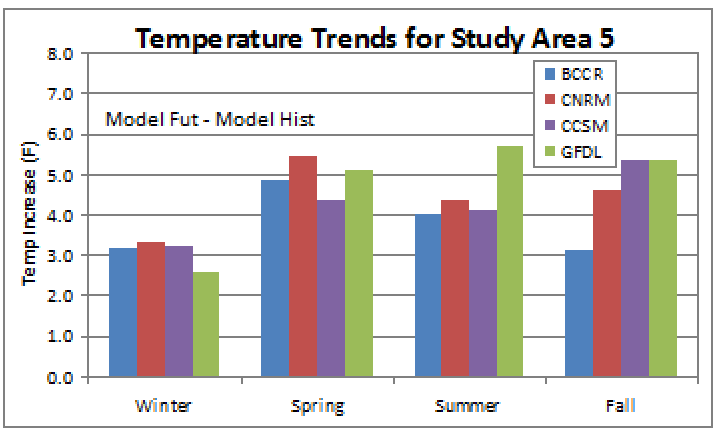


Figure C.20: Comparison of GCM precipitation trends for Study Area 5 (Far West).

D. Responses to Comments from Texas Water Development Board

TEXAS TECH UNIVERSITY
Edward E. Whitacre Jr. College of Engineering
Water Resources Center

Memorandum

To: *Texas Water Development Board*

From: *Dr. Spandana Tummuri*

Date: *01/30/2013*

Subject: *Responses to "Review Comments on Draft Final Report "Assessment of General Circulation Models for Water-Resources Planning Applications" by Spandana Tummuri, David B. Thompson, Ken A. Rainwater - TWDB Contract No. 0904830938"*

The purpose of this memorandum is to summarize the responses for the review comments provided by Texas Water Development Board upon the review of the draft report "Assessment of General Circulation Models for Water-Resources Planning Applications". The responses discussed in this memorandum were included in the final report. One (1) electronic copy and six (6) bound double-sided copies of the final report were delivered to Texas Water Development Board.

Texas Tech University Water Resources Center
Box 41022 | Suite 203 Civil Engineering Building | Lubbock, Texas 79409-1022
T 806.742.3597 | F 806.742.3449

ATTACHMENT I - Review Comments on Draft Final Report "Assessment of General Circulation Models for Water-Resources Planning Applications" by Spandana Tummuri, David B. Thompson, Ken A. Rainwater TWDB Contract No. 0904830938

General

The report meets the general study objectives of applying a systematic approach to identifying an appropriate set of General Circulation Models (GCMs) for use in Texas, and of recommending appropriate techniques for downscaling GCM output for use in water supply analyses.

Major Comments

1. The report provides quantitative support for the strong connection between El Nino/La Nina (ENSO) with temperature and precipitation anomalies in Texas (Figs. A.1-A.6), suggesting that GCMs that model this global scale feature well might also do well in modeling temperature and precipitation in Texas. The approach taken in the report for selecting GCMs for Texas, however, is to focus on the Jet Latitude Index (JLI), a measure of the location of the polar front jet. Justification for the focus on JLI by presenting similar quantitative evidence of the relationship between JLI and temperature and precipitation anomalies in Texas would help the reader better understand the need to focus on JLI rather than ENSO. Better explanation of the computation procedure for JLI would also help.

Response: Additional clarification provided in the report.

2. Executive Summary, page i, last paragraph: Please explain why other forcings are of less interest than greenhouse gas in this study.

Response: Major forcings impacting the climate are natural forcings such as solar energy output, volcanic variations, and man-made forcings due to greenhouse gas variations. Models that use the natural forcings are able to closely match paleoclimate record of temperatures for the last 100 years. When greenhouse gas forcings are excluded, the models fail to simulate the warmings of the 20th century, even though the simulations of the preceding centuries using only natural forcings were successful. Therefore, one forcing of particular interest when simulating future climate is the change in greenhouse gas (GHG) concentration as a function of time and human activity.

3. Executive Summary, page ii, second paragraph: the WRAP has not been updated to process climate-change driven hydrology, nor has regionally-downscaled GCM data been used to adjust naturalized flows to our best knowledge but if authors are aware of such effort then please indicate the individuals or organizations who have done that.

Response: The downscaled information currently available is not directly usable in the water availability model (WAM) used by Texas water resources engineers. An interface between the projected climate variables and WAM is required. The downscaled GCM projections should be input to a hydrologic model that can then provide the appropriate input to the WAM.

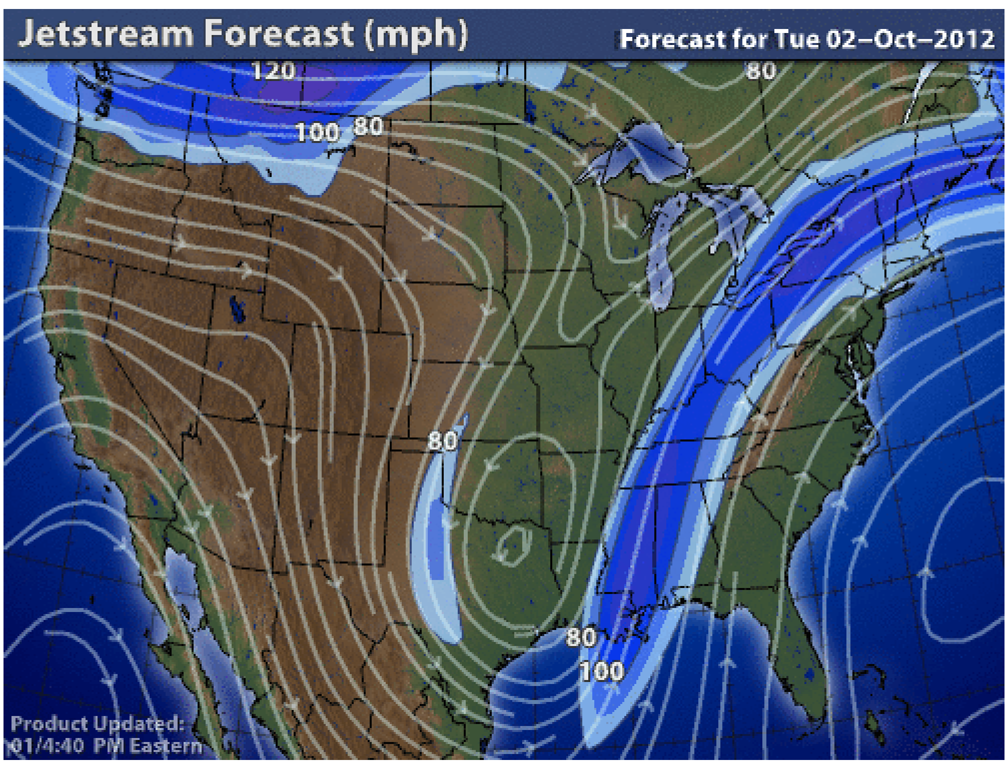
The official water availability model for Texas, the Water Rights Analysis Package (WRAP) was used to run a test case scenario for incorporating climate change impacted hydrologic information into the water availability estimation. Output from a GCM (CCCMA) was used to adjust input to a watershed hydrology model (Soil and Water Assessment tool, SWAT). Net evaporation rates were also adjusted for the future climate scenario by using data from the GCM. Naturalized flows and net evaporation were obtained by running the SWAT using projected 2050 climate change scenario IS92a. Thus flow and evaporation values obtained from the watershed model, SWAT, are used to adjust WRAP inputs. WRAP was then run with the historical and projected climate change data from the SWAT tool to assess the uncertainty in the future water availability due to climate change. The results of the study indicated that water supply capabilities change significantly for 2050 climate conditions. (Wurbs and others, 2005).

4. Executive Summary, page iii, last paragraph: This paragraph seems to contradict earlier statement on WRAP (page ii, second paragraph). Please clarify.

Response: Fixed earlier paragraph to address the contradiction.

5. Appendix B. Please explain why the jet stream pattern for Area 2 is so different than all other areas.

Response: This is because the polar jet stream curves in the region covered by study area 2 and the path traversed by the wind currents undergoes a change. Please see figure below that depicts the phenomenon.



<u>Figure Courtesy: Weather Channel</u>

6. Page 41, "months with more than one jet ...were eliminated". Please explain why multijets disqualify a month.

Response: Some screening procedures were built into the JLI identification program. The purpose of the screening procedures was to help identify odd occurrences of JLI and eliminate months with these occurrences. For some months, a strong and singular regional jet stream was not clearly identifiable. These months were not included in the JLI analysis. Analysis for some other months resulted in more than one jet. Jet streams are fast flowing, relatively narrow air currents found in the atmosphere around 7 miles above the surface of earth. For a given month, there can be only one average latitudinal location with strong wind currents. If a given month has more than one jet, that suggests error in the data set for that month. Hence the data for that month was not included in the analysis for the calculation of the latitudinal location of jet stream. For any given month, the JLI was not assigned if the observed maximum zonal wind velocity at one longitude was greater than 12^O north or south from the maximum zonal wind velocity observed at any other longitude. If the latitudinal locations are 12^O apart, the JLI at two longitudes might be referring to two different maximum wind currents and not the same one. These automated screening procedures were proven to be effective at removing most months lacking a clearly distinct jet or having more than one predominant jet within the index domain.

7. Page 41, " ...For any given month, the JLI was not assigned if observed maximal zonal wind velocity at one longitude was greater than 12 degree north or south from the maximum zonal wind velocity observed at any other longitude". Please explain why this criterion was set.

Response: Some screening procedures were built into the JLI identification program. The purpose of the screening procedures was to help identify odd occurrences of JLI and eliminate months with these occurrence. For some months, a strong and singular regional jet stream was not clearly identifiable. These months were not included in the JLI analysis. Analysis for some other months resulted in more than one jet. Jet streams are fast flowing, relatively narrow air currents found in the atmosphere around 7 miles above the surface of earth. For a given month, there can be only one average latitudinal location with strong wind currents. If a given month has more than one jet, that suggests error in the data set for that month and hence the data for that month was not included in the analysis for the calculation of the latitudinal location of jet stream. For any given month, the JLI was not assigned if the observed maximum zonal wind velocity at one longitude was greater than 12^O north or south from the maximum zonal wind velocity observed at any other longitude. If the latitudinal locations are 12^O apart, the JLI at two longitudes might be referring to two different maximum wind currents and not the same one. These automated screening procedures were proven to be effective at removing most months lacking a clearly distinct jet or having more than one predominant jet within the index domain.

8. Page 50, " ...0.6 inch/month for precipitation and 3F for temperature ...)". Please explain how the threshold values of 0.6 and 3 are determined.

Response: Threshold values were selected by the project team and represent approximately 30% of the maximum value.

9. Please explain why the sub-tropical jet is not considered.

Response: The project team conducted a sensitivity analysis to confirm the impact of fluctuations in polar *jet stream movement on the precipitation and temperature changes in the study area. Once this link was ascertained, the polar jet stream was identified and used as the large scale climate feature. There was not enough time and budget available to perform similar sensitivity analysis for the sub-tropical jet stream to determine if that could be used as large scale climate feature instead.*

10. This work demonstrated that four GCMs provided excellent results for four of the five study areas in Texas (see Table 5.2 on page 42). Please provide author's opinion on whether it is better to 1) use these four models to make projections for the entire state or 2) use a different set of models depending on the area of the state and what models for what areas.

Response: Added clarification in the "Conclusions" section.

11. On page 50 of the report, the following statement is made: "The GCM-predicted magnitudes of both precipitation and temperature values were comparable to observations recorded for the regions covering the study areas." Please provide data or figures demonstrating how well output from the selected GCMs compared to observed precipitation and temperature data for the Study Areas.

Response: Upon further consideration, we have decided to remove this statement from the report.

12. The report makes a number of recommendations but no clear path forward is articulated. Please provide specific recommendations of how to move forward in incorporating GCM results (and uncertainty) into water planning for Texas. Specifically, what path should be followed in order to capture the most likely future conditions in each of the study areas? If the authors are uncomfortable recommending anyone option (or set of options) for each of the study areas, this should be clearly documented in the report.

Response: Added clarification in the "Conclusions" section.

Reviewers noticed that the report mentioned some options but it is not always clear if they are recommended. See some of the examples below for Study Area 1 (East Study Area): 1) Use the results of a single GCM (CCSM, GFDL, BCCR, or CNRM). From page 55, Recommendation l(b) of the report, this option is deemed "not appropriate." 2) Use ensemble results from three GCMs whose results converge (CCSM, GFDL, and BCCR) for both temperature and precipitation. On page 54, the authors state that these models "can be used for more similar ensemble analysis." It is unclear if this is the recommended option in order to obtain the "most likely" future conditions for Study Area 1. 3) Use of ensemble results from four GCMs, where the results of one (CNRM) diverge from the other three (CCSM, GFDL, and BCCR) in terms of precipitation. On page 54, the authors state that use of ensemble results from all four models would "represent greater overall uncertainty." It is unclear if the authors believe this option would be superior to option 2 above. 4) Use of downscaled results from one of the recommended GCMs (CCSM, GFDL, BCCR, or CNRM). On page 55, Recommendation 2(c) states that this option "is most often used to obtain estimates of meteorological variables used in water resources and hydrologic modeling." If this option is selected, the authors recommend downscaling be accomplished by means of a bias-corrected statistical approach (page 52). However, it is unclear if they believe this is the best option for water planning for Study Area 1. 5) Use of downscaled results from all four of the recommended GCMs (CCSM, GFDL, BCCR, and CNRM). Results from individual downscaled GCMs could be combined in some manner or processed separately in order to obtain possible future conditions for Study Area 1. On page 56, the report says: "It is preferable to use an ensemble approach to average the downscaled GCM data for the models selected in this study instead of selecting one or the other models." It would be helpful if the authors could describe the approach, if it is known. For example, should downscaled GeM results be combined and then one set of ensemble results run through a hydrologic model in order to identify impacts on water supply? Or, should results from each downscaled GCM be run through a hydrologic model and then the impacts on water supply combined in order to obtain a most likely impact? If it is not clear which of these paths would be best, that should be noted in the report.

Response: Made changes to the report to clarify the recommendations.

Page 42, 3rd paragraph, 3rd sentence. "From Table 5.2, four models were common to the five study areas." This statement appears to be incorrect. From Table 5.2, only two models were common to all five study areas, namely GFDL and CNRM. Two other models (CCSM and BCCR) were common to four of the five study areas. One model (CSIRO) was common to two of the five study areas. And three of the models provided superior representation for only one of the study areas (HADCOM, PCM, CGCM). While the four models selected for further analysis appear adequate (CCSM, GFDL, BCCR, and CNRM), the documentation should more accurately described why they were chosen. Please consider rewriting this description.

Response: Made changes to the report to clarify the recommendations.

13. The authors described several approaches to downscaling, including dynamic and statistical downscaling and weather generators. They provide descriptions of each of these methodologies. However, their recommendation regarding appropriate methodology reads more like an observation (page 55, recommendation 2(c)): "Statistical downscaling using gridded data and bias correction is most often used to obtain estimates of meteorologic variables used in water resources and hydrologic modeling." Please make a definitive statement (or describe why one should not be made) regarding the appropriate methodology for downscaling.

Response: Made changes to the report to clarify the recommendations.

<u>Minor Comments</u>

1. Page 7, first sentence. Please explain when C02 levels will be assumed to peak at 475 ppm.

Response: Based on the CO_2 projections described in IPCC SRES report, on an average, CO_2 levels are generally assumed to peak at 475 ppm by the middle of this century and stabilize at 400 ppm by the end of the century (IPCC, 2007). There is not one precise number because the sensitivity of the climate system to the greenhouse gases is quantified differently for each emission scenario and cannot be estimated exactly.

2. Page 7, third sentence, beginning "The basic premise ...". This statement gives the impression that climate modelers assume *a priori* that GHGs will cause climate change. Rather, the basic premise of climate modeling is that the physical and chemical processes that affect climate can adequately

be described by mathematical constructs embedded in GCMs, and that the models can provide a means to quantitatively compare the effects that GHGs have in influencing climate against other influences. Please clarify this statement.

Response: The basic premise of climate modeling is that the physical and chemical processes that affect climate can be adequately described by GCMs. GCMs provide a means to quantitatively capture and represent the effects that GHGs have in influencing climate.

3. Page 21, first paragraph. Please explain what "screen height temperature" means.

Response: Clarification added in the report.

4. Page 27, Section 3.6. The definition of Jet Latitude Index (" ... the mean position of the polar jet front") leaves the reader with the impression that a single JLI, corresponding to the location of the jet stream trough could be identified for a large region, say the state of Texas. Please provide explanation on the steps taken to compute the JLI, and please explain why a region like Texas would have more than one JLI.

Response: A JLI can be located for as many study areas as required. JLI represents the mean position of the polar jet front for a given study area defined in the analysis. One JLI per study area was identified for this project. Description of why five study areas were used to represent state of Texas is provided in report "Task 1.1.1 - Assessment of GCMs-Selection of Study Areas-20101014.pdf".

5. Page 34, par. 1. Please explain what is meant by "conservative representation". Is it conservative in that GHG estimates are high, or low?

Response: Changed the terminology to balanced (mid high/mid low).

6. Page 38, last paragraph. Please provide references to support the statement "After detailed review of the literature, it was observed that the polar jet stream ... ", and for the statement "Oscillation of water temperature ... for 100,000 years".

Response: Included references.

7. Page 40, first paragraph. Please provide references to support the statement "The two endpoints ... affect the location of the polar jet stream".

Response: Included references.

8. Page 40, second paragraph. The first sentence states that the GCMs were "evaluated for their abilities to reproduce the real-time movement of the polar jet stream", but the selection process relies on visual comparison of 30-year monthly mean positions of the polar jet stream. Please clarify the first sentence.

Response: The GCMs comparison process was based on a visual comparison of seasonal variation of the latitudinal location of the polar jet stream.

9. Page 44, Figures 5.2, and subsequent figures in Appendix B. Please include the ensemble average line for the four selected models in the second figure of all sets. Please explain the grey shading shown for the NCEP REAN data.

Response: Monthly location of jet stream for climate models are represented by different shapes and colors. Real-time representation of the jet stream location by NCEP/NCAR reanalysis dataset is indicted by means of a red line with grey error bars (5%). Model ensemble is shown by means of a black dotted line.

10. Page 62, first sentence. Please provide references for literature reviewed.

Response: Included references.

11. Page 70 -76, Figures A.7 -A. 13. Please provide explanation and discussion for these figures in the body of the text.

Response: Figures are not relevant in the appendix and have been accidentally included in the appendix. The figures were created for an analysis that was performed to determine the need for a fifth study area. Now they have been removed from the report.

12. Page 81, Figure *BA.* The symbols shown in the figure do not agree with models listed in Table 5.2. Please correct.

Response: Revised Table 5.2

Study Area Region GCMs Selected
Study Area 1 Eastern CCSM, GFDL, BCCR, CNRM
Study Area 2 Southern CCSM, GFDL, BCCR, CNRM, HADCM, PCM, ECHAM, CGCM, IPSL
Study Area 3 Western CCSM, GFDL, BCCR, CNRM
Study Area 4 Northern CCSM, GFDL, BCCR, CNRM, HADCM, PCM, CSIRO
Study Area 5 Far West GFDL, CNRM, CSIRO, CGCM

13. Page 83, Figure B.6. Please explain why no range is shown for NCEP REAN data for July and August.

Response: Sufficient data was not available for those months.

14. Page 86 -figure B.9. Please include the model ensemble in the figure to be consistent with the figures shown for other areas.

Response: Addressed the comment and included revised figure.

Editorial Comments

1. Page i, par. 3 and page 1, par. 3 -Please change "Water supply planning in Texas is governed by ..." to "Water supply planning in Texas is overseen by ..."
2. Page iii, par. 2, next to last sentence beginning "The projects for CCSM 3.0 .." -Please change " ... model from those ..." to " ... model differ from those ...".
3. Page iii, last par., last sentence -Please change "an hydrologic model" to "a hydrologic model".
4. Page 6, par. 1 -Please change "gases trap the re-radiate energy."to "gases trap and reradiated energy".
5. Page 14, second sentence -Please change "A GCM" to "GCMs", "represents" to "represent", and "was selected" to "were selected".
6. Page 18, first paragraph -Please change "time-varying" to "time-varying" (remove space).
7. Page 26, first paragraph -Please change "temperature is be projected" to "temperature is projected" .
8. Page 42, par. 3 -Please change "four models were common to the five study areas" to "two models were common all five study areas, while the remaining two were common to four of the five areas.". Neither the CCSM model nor the BCCR model was selected for Study Area 5.
9. Page 46, par. 1 -Please change "National Air and Space Administration" to "National Aeronautics and Space Administration"
10. Pages 99-101, Figures C.11 to C.16 -Please change the figure labels from "Study Site" to "Study Area"
11. Executive Summary, page i. 3rd paragraph, 1st sentence. Water supply planning in Texas is described as being "governed" by the Texas Water Development Board. It would be more accurate to say "The regional and state water supply planning process in Texas is administered by the Texas Water Development Board." Same comment applies on page 1.
12. Executive Summary, page i. 3rd paragraph, 3rd sentence. "TWDB personnel produce a State Water Plan over the five year duration of the planning cycle" should be replaced with "A new State Water Plan is produced over the five year duration of each planning cycle." Same comment applies on page 1.
13. Executive Summary, page iii. 2nd paragraph, 8th sentence. "The projections for CCSM 3.0 model from those of the other GCMs." The meaning of this sentence is unclear. Please reword as necessary to convey the intended meaning. Same comment applies on page 1.
14. Page 6, 1st paragraph, 11th sentence. "Hence, an appropriate representation of the complex physical processes that contribute to must include the impact of GHG emissions." This is an incomplete sentence. Please reword as necessary to convey the intended meaning.
15. Page 12, 1st paragraph, last two sentences. Suggest rewording to remove phrase "in climate modeling world." Perhaps the following sentence could replace the meaning of both sentences: "The effect of EI Nino events on other regions of the globe is an example of teleconnection, when weather anomalies in one region are related to climate variations at a remote location."
16. Page 25, 4th paragraph, 1st sentence. "... based the approach developed for regional studies ..." Meaning of the sentence is unclear. Please reword.

Response: Addressed all editorial comments.

<u>Typos</u>

There are a few typos in the document. Please proof read and correct problems similar to the non-exhaustive list below (additions underlined, deletions struck through):

1 Cover. "February 27, 20-l-U2."

2 Executive Summary, page i, 4th paragraph, 1st sentence. ""to track the movement at of the atmosphere." Same comment applies on page 1.

3 Page 5, 1st paragraph, 3rd sentence. "impacted by the-changes in the climate."

4 Page 6, 1st paragraph, 8th sentence. "the existence of the-human life."

5 Page 6, 1st paragraph, 10th sentence. "a rate substantially greater than 1°F per yeaf£entury. "

6 Page 18, 3rd paragraph, 4th sentence. "the parameter§. that describe."

7 Page 19, 5th paragraph, 1 st sentence. "from a river easeabasin was examined."

8 Page 19, 5th paragraph, 2nd sentence. "They examined runoff."

9 Page 56, paragraph numbered "5", 1 st sentence. "inputs toe-for a given watershed."

Response: Corrected the typos.