Water Availability in a Warming World

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ABSTRACT

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As climate warms during the 21st century, the resultant changes in water availability are a vital issue for society, perhaps even more important than the magnitude of warming itself. Yet our climate models disagree in their forecasts of water availability, limiting our ability to plan accordingly. This thesis investigates future water availability projections from Coupled Ocean-Atmosphere General Circulation Models (GCMs), primarily using two water availability measures: soil moisture and the Supply Demand Drought Index (SDDI).

Chapter One introduces methods of measuring water availability and explores some of the fundamental differences between soil moisture, SDDI and the Palmer Drought Severity Index (PDSI). SDDI and PDSI tend to predict more severe future drought conditions than soil moisture; 21st century projections of SDDI show conditions rivaling North American historic mega-droughts. We compare multiple potential evapotranspiration (EP) methods in New York using input from the GISS Model ER GCM and local station data from Rochester, NY, and find that they compare favorably with local pan evaporation measurements. We calculate SDDI and PDSI values using various EP methods, and show that changes in future projections are largest when using EP methods most sensitive to global warming, not necessarily methods producing EP values with the largest magnitudes.

Chapter Two explores the characteristics and biases of the five GCMs and their 20th and 21st century climate projections. We compare atmospheric variables that drive water
availability changes globally, zonally, and geographically among models. All models show increases in both dry and wet extremes for SDDI and soil moisture, but increases are largest for extreme drying conditions using SDDI. The percentage of gridboxes that agree on the sign of change of soil moisture and SDDI between models is very low, but does increase in the 21st century. Still, differences between models are smaller than differences between SDDI and soil moisture projections.

Chapter Three addresses the three major differences between SDDI and soil moisture calculations that shed light on why their future projections diverge: evaporation approximations, dependence on previous months’ conditions, and the inclusion of additional variables such as runoff. We implement various changes in SDDI and a GCM vegetation scheme to test the sensitivity of each measure and to evaluate which alterations increase the similarity between SDDI and soil moisture.

In addition to deconstructing the differences between SDDI and soil moisture, we analyze their projections regionally in Chapter Four. In seven regions (the southwest U.S., southern Europe, eastern China, eastern Siberia, Australia, Uruguay and Colombia), we 1) assess the forecasts of future water availability changes, 2) compare the atmospheric dynamical processes that produce rainfall and drought in the real world to the way it occurs in individual GCMs, 3) determine how these processes change as global temperatures increase, and 4) identify the most likely scenarios for future regional water availability.

Chapter Five summarizes key findings by chapter, enumerating this dissertation’s contributions to the field. It then discusses the limitations of existing models and measures, and suggests potential solutions for overcoming their predictive shortfalls.
Finally, the chapter concludes with a proposal for future research to expand upon this dissertation work.

This thesis highlights the global and zonal differences between two water availability measures, SDDI and soil moisture and identifies regions where they agree and disagree in 21st century modeled scenarios. It provides an explanation for differing projections in soil moisture and SDDI and proves that it is possible to bring convergence to their future projections, which is also applicable to PDSI. Finally, a detailed analysis of climatic changes from five GCMs made it possible to present the most likely scenarios for 21st century water availability in seven regions.
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FOREWORD

Not many natural disasters are as insidious as drought. They often begin mildly and take place over long periods of time. For this reason, they are commonly overlooked, although impacts can be felt in many sectors (e.g. health, agriculture, ecosystems, recreation and industry, etc.). Disease, crop failure, famine, forest/bush fires, heat waves, economic loss, infrastructure failure are just a few repercussions of a sustained decrease in water availability. Although drought is not a short timescale event like many natural disasters (e.g. hurricanes, tornadoes, tsunamis, floods, fires, and earthquakes), they do share a common trait; drought is a product of an overabundance of energy. They are frequently triggered by excess evapotranspiration and changes in atmospheric dynamics, such as downwelling or a shift in the ITCZ.

My thesis research was motivated by the potential impacts of anthropogenic drought forced by increased greenhouse gases. As surface air temperatures increase over the 21st century, the water-holding capacity, specific humidity and the evaporative demand (i.e. potential evapotranspiration) of the atmosphere rise as well. There is some expectation that dry areas will become drier and wet areas will become wetter [Held and Soden, 2006]. However, it should be noted that IPCC AR4 GCM soil moisture projections show very little agreement among models, which is an additional motivating factor for this research [IPCC, 2007]. The influence of climate change on drought will be exacerbated by global population growth and increasing per capita water demands due to urbanization and industrialization. The potential societal and environmental impacts of widespread water availability changes projected by climate models have left researchers with an increased sense of obligation to communicate with the public.

There is a general consensus that as a community, drought researchers are doing an insufficient job communicating with stakeholders, which not only include farmers and ranchers
but also water managers, city and state planners, decision makers, the media, the energy sector, industry and of course, the public. In some cases, specific user needs are known but in many cases ongoing dialogue needs to continue to identify currently unspecified needs. Unfortunately, in many cases, stakeholders’ predictive needs may never be met due to model limitations. However, some could be easily accommodated; a common suggestion to researchers is the need to translate scientific terms to every-day scenarios that resonate with the public. An effective method, which will be used in this thesis, is translating science to understandable language through discussion of regional potential impacts.

An important differentiation between stakeholder groups is the for need information on different time scales. For example, farmers and ranchers are likely to need monthly and seasonal predictions while city and state planners may find information on yearly or decadal timescales to be of more interest. The following study will be of most utility to users with long-term interest in water availability changes.

In addition to research motivated by stakeholders, curiosity-driven science, which is unregulated by user needs is also of critical importance for innovation and should not be undervalued. My research on water availability is a mixture of both curiosity-driven science intended for an audience of fellow drought researchers and user-driven research, which while also satisfying to the curiosity, should be beneficial to long-term water availability change stakeholders. In reality, stakeholders need much more than a rewording of science; they need an understanding of their risks and the capacity to mitigate them, which indicates that a larger community needs to be involved.

*Dissertation Overview*
My research has been divided into four parts and a final summary. Chapter 1 addresses the various techniques for measuring water availability, with a focus on soil moisture, drought indices and potential evapotranspiration calculation methods. Chapter 2 gives an overview of GCM characteristics and biases along with their global and zonal projections of future water availability. Chapter 3 discusses the reasons that water availability measures differ and which aspects can be altered to make them more similar. Chapter 4 is a look into regional future water availability projections and the potential mechanisms causing GCM and water availability measure agreement and disagreement. The final chapter is a summary of key findings and future work.
1 Measures of Water Availability

1.1 Introduction

The ability to access sufficient amounts of fresh water is a requirement for any human settlement. In dry regions, water is moved in from more fluvial areas or withdrawn from reservoirs that are refilled during wet periods. A threat arises when water is withdrawn at an unsustainable rate. This is a familiar threat to many communities across the globe today and it has been throughout history. This threat is likely to become even more severe and widespread in the 21st century.

The Intergovernmental Panel on Climate Change (IPCC) reported widespread agreement among climate model projections on emerging patterns in the global hydrologic cycle in the 21st century, such as increased precipitation at high latitudes, decreased precipitation in the subtropics and increases in the frequency of heavy precipitation events, all of which would lead to permanent changes in annual and seasonal runoff and groundwater recharge. These changes in the hydrologic cycle could fundamentally alter the nature of drought and flooding in many regions. In areas that are currently using all of their available water resources, these changes could prove devastating.

In addition to precipitation changes in the 21st century, rising temperatures are likely to impact evaporation as well [IPCC, 2007]. According to the Clausius-Clapeyron equation, every 1°C increase in temperature increases the water-holding capacity of the atmosphere by approximately 7%. As temperatures increase, the atmosphere is able to hold more water vapor; a global increase in atmospheric moisture demand is projected. Today’s water availability deficits invariably result from decreased precipitation, but in the future this may no longer be the case.
Future droughts may occur primarily because of temperature increases, and may even feature increased precipitation. This is why looking at projected changes in precipitation alone is not enough.

Precipitation and evaporation are not expected to change uniformly across the globe. Hydrologic changes will be different in every region and are highly dependent on local topography and water resources. Areas dependent on spring snowmelt may find that increased temperatures cause snow to melt earlier or precipitation that used to fall as snow has changed to rain. In either scenario, the expected arrival of fresh water is altered in a way that may leave communities vulnerable to water shortages.

In addition to global warming exacerbating water availability, growing populations and wealth are also creating an increase in societal demand for water. In these regions, as well as others, a means of quantifying the global distribution of available water with respect to future climate simulations is needed to raise awareness in areas likely to experience an increase in drought extent or severity due to global warming.

There are many ways to define drought. Simply looking at the change in precipitation does not take into account changes in evapotranspiration or vegetation, which are sensitive to temperature changes and therefore likely to influence 21st century climate. A study by Burke and Brown [2008] found significant differences in doubled CO₂ drought projections when using different measures. This chapter continues in the same vein and focuses on two types of water availability measures: soil moisture and drought index values, specifically the Supply Demand Drought Index (SDDI) [Rind et al., 1990] and the Palmer Drought Severity Index (PDSI) [Palmer, 1965]. The SDDI is calculated using monthly precipitation and temperature, which are available for most of the past century over much of the world. PDSI requires additional inputs
that are often unavailable globally. Although, efforts have been made to create a PDSI that could be used globally; Wells et al. [2004] created a self-calibrating PDSI (SC-PDSI) that replaces the empirically derived constants in the formulation with dynamically calculated values.

More than drought index inputs, it is soil moisture measurements that have proven to be more elusive. Many countries do not share hydrologic data. In addition, measuring soil moisture is a difficult task since values can vary significantly over small areas. That is why it is difficult to compile global datasets that are not sparse or infrequently sampled. This has led the agricultural industry to rely heavily on drought indices [Robock et al., 1998; Henderson-Sellers et al., 2002; Henderson-Sellers et al., 2003; Varis et al., 2004]. Today, when using Coupled Ocean-Atmosphere General Circulation Models (GCMs) to model future climate, we have soil moisture projections and the variables needed to compute drought indices, both of which can be used for studying future drought.

This chapter is devoted to soil moisture and drought index comparisons. Section 1.2 discusses both modeled and observed soil moisture data from GCMs, Land-Surface Models (LSMs), satellites and ground-based stations. In section 1.3, SDDI and PDSI formulations are discussed and the two measures are compared in the 20th century in North America calculated with both modeled and observed temperature and precipitation. In section 1.4, various methods of calculating potential evapotranspiration are discussed and multiple methods are compared in New York using input from the GISS Model ER GCM and local station data from Rochester, NY. Finally, SDDI and PDSI values calculated using various potential evapotranspiration methods are compared.
1.2 Soil Moisture

In theory, soil moisture provides the most essential information needed for drought determination. However, there is a lack of long-term (i.e. >50 years) global soil moisture measurements. As mentioned above, it is not only global soil moisture measurements that are lacking, meaningful local ones are also hard to come by. Measuring soil moisture is extremely difficult because of the great heterogeneity that exists on small spatial scales. It is for those reasons that modeled soil moisture is often used for climate research. Modeling land surface processes to obtain soil moisture is a more indirect approach than in situ or remotely-sensed measurements but it is often necessary. There is no standard among models on how it is defined; each model has their own method. The land-surface schemes of the GCMs used in this study are described in Table 1.1. The soil and vegetation is divided into multiple layers of varying thicknesses with varying physical regulations, which make inter-model comparisons difficult. Disagreements are often overlooked as long as latent heat flux and evapotranspiration values are reasonable [Shaake et al., 1996; Dirmeyer, 2004; Cornwell and Harvey, 2007]. However, Robock et al. [1998] point out that plants care about the soil moisture values, not the fluxes.

Although there are many problems with soil moisture consistency among models, this may be changing. Many satellite instruments that have been launched over the last decade have the ability to remotely sense surface soil moisture. However, global surface soil moisture datasets are not enough; soil moisture down to the root zone is needed to understand changes in vegetation. Over the next decade, NASA’s Soil Moisture Active-Passive (SMAP) satellite should provide the first global root zone soil moisture measurements, which will likely be used to calibrate models.
1.2.1 Soil Moisture Datasets

Land-Surface Models (LSMs)

Table 1.2 lists four 1-degree stand-alone LSMs that were run between 1979 and 2010 using forcing from precipitation gauge observations, satellite data, radar precipitation measurements and output from numerical prediction models. Soil moisture output from each of the LSMs was collected from the Global Land Data Assimilation System (GLDAS) [Rodell et al., 2004].

Coupled Ocean-Atmosphere General Circulation Models (GCMs)

Soil moisture output was gathered from five GCMs using two sets of experiments performed for the IPCC 4th Assessment Report: the Climate of the 20th Century experiment (20c3m) and the SRES A2 experiment for the 21st Century. The model output was provided by Lawrence Livermore National Laboratory’s WCRP CMIP3 multi-model database. Table 1.1 lists the five models used as well as a description of each model’s land-surface scheme.

Satellite Instruments

As mentioned above, remotely-sensed surface soil moisture from satellite instruments is now available for most of the past two decades thanks to the ERS-Scat as well as other instruments that have launched since. Table 1.3 lists satellites with soil moisture retrieving ability. Data from these missions is not included in this soil moisture comparison because the measurements are limited to the moisture in the top ~1cm of soil/vegetation. Nonetheless, Rüdiger et al. [2009] have shown that AMSR-E (VUA-NASA) and ERS-Scat have a good correlation with reanalysis LSM predictions. Total water storage data is available from the Gravity Recovery and Climate Experiment (GRACE) satellite using gravity field retrievals. This data is currently being used to
understand continental hydrologic systems. However, it does not only represent soil moisture but all terrestrial water including groundwater storage, which adds complications for evaluating shifts in root-zone soil moisture.

\textbf{In Situ Measurements}

The International Soil Moisture Network [ISMN, 2010] has collected in situ soil moisture measurements from many stations around the world in Australia, Spain, France, Italy, China, Mongolia, USA and Russia to a depth of up to 0.3 meters. Interpolating a global dataset from these sites remains infeasible. However, measurements from these stations are compared to modeled soil moisture data on a regional basis in Chapter 4.

\textbf{1.2.2 Soil Moisture Datasets Comparison}

Comparing soil moisture time series truly illustrates how different the models are. Average global soil moisture ranges from 400 to 800 kg/m\(^2\) in the four GLDAS LSMs (Figure 1.1), which is a much tighter range than we see in the five GCMs (Figure 1.2). [Note: Antarctica is not included in calculations for Figures 1.1 or 1.2 and Greenland is not included in Figure 1.2.] There is similar annual variability in the Mosaic, NOAH, and VIC LSMs, which is much larger than in CLM. In the former three models, there is also a bump in global soil moisture between approximately 1994 and 1998 due to a strong El Niño in 1997-1998 and a strong La Niña in 1998-1999. CLM may behave differently from the other LSMs because of it has close to three times as many soil layers (Table 1.2). However, all four LSMs show a noticeable multi-decadal downward trend over the full time period shown.

In Figure 1.2, the GCMs display a much broader range in the amount of water in the soil, from 50 to 1300 kg/m\(^2\) due in large part to the different model definitions of soil moisture depth.
The two GCM outliers are MIROC, which has much more soil moisture than the rest and GFDL, which is much lower. The differences between the GCMs are dependent on the depth to which soil moisture is defined. The interannual variability of all of the models is relatively small compared to differences between models. Coincidentally, the average global GCM soil moisture is roughly equal to the average global LSM soil moisture (~600 kg/m²).

The percentage change from the 1979-1989 average gives a better picture of how the long-term changes compare in the different models (Figures 1.3 and 1.4). Figure 1.3 shows that all GCMs except CCCma are losing soil moisture with time. GFDL and HadCM3 show a noticeable decline. The reason for the large decline and variability in GFDL in Figure 1.3 is the relatively small absolute soil moisture values (Figure 1.2). A small change in GFDL soil moisture registers as a relatively large shift as a percentage change. HadCM3 exhibited the largest long-term decline in soil moisture of all of the GCMs. However, the 1979-2010 trends in LSM soil moisture show a global decrease in soil moisture that is much stronger than what we find in GCM output for the same period. This could be due to LSMs overestimating $E_P$ as suggested by Milly and Dunne [2011]. However, if LSMs overestimate $E_P$, their soil moisture values may be expected to be lower than GCMs, which in general they are not. It is possible that the LSMs have a higher sensitivity to temperature changes. If the 1979-2010 LSM trends continued through 2100, the LSM anomalies would reach soil moisture anomalies ranging from -109 to -393 kg/m² that are much more severe than the GCM projections.

The discrepancies between data sets and the lack of a multi-decadal global in situ data strongly support the need for exploring supplemental water availability measures. With issues as important as access to fresh water at stake, it is unwise to rely on soil moisture alone to highlight global warming-induced changes in the hydrologic cycle.
1.3 Drought Indices

Across the world, farmers, researchers, journalists and policy makers use drought indices to simplify hydrologic conditions and quantify drought severity using frequently limited data. There are many drought indices to choose from. This study focuses on the PDSI and a PDSI-derivative index, the SDDI.

**Palmer Drought Severity Index (PDSI)**

The most common meteorological drought index in the United States is the PDSI [Palmer, 1965], which ranges from -10 (driest) to +10 (wettest).

\[
PDSI(i) = 0.897PDSI(i-1) + \frac{Z_{PDSI}(i)}{3}
\]  \[1.1\]

where

\[
Z_{PDSI} = K d_{PDSI}
\]  \[1.2\]

\[
d_{PDSI} = P - (\alpha E_p + \beta R_p + \delta RO_p - \varepsilon L_p)
\]  \[1.3\]

K is a weighting factor dependent on the average local water supply and demand and

\[d_{PDSI}\] is the potential evapotranspiration, \[R_p\] is the potential recharge, \[RO_p\] is the potential runoff and \[L_p\] is the potential soil moisture loss. The coefficients \[\alpha, \beta, \delta\] and \[\varepsilon\] are the ratios of actual to potential values for evapotranspiration, recharge, runoff and soil moisture loss respectively. They have been generated for the U.S. using observations but are not available globally, which limits large-scale studies using PDSI. Dai et al. [2004] created a global PDSI dataset for the years 1870-2002. However, PDSI coefficients were tuned to U.S. soil characteristics.

**Supply Demand Drought Index (SDDI)**
Another approach to estimating a surplus or deficit of soil moisture is calculating the difference between precipitation (the atmospheric supply) and potential evapotranspiration (the atmospheric demand), which is the basis of the SDDI. SDDI requires monthly mean precipitation and temperature as inputs for each location without requiring regional coefficients needed for the widely used PDSI. SDDI can be calculated globally and is highly correlated with PDSI in the United States [Rind et al., 1990].

SDDI was calculated using the change in the differences of precipitation (P) and potential evapotranspiration (EP) between the future run and the average of the control run for each grid box.

\[
d_{\text{SDDI}} = P - E_P - (P - E_P)_{\text{ctrlave}}
\]  

[1.4]

where EP is calculated using the Thornthwaite method described above. Z, the “SDDI moisture anomaly index” is defined as

\[
Z_{\text{SDDI}} = \frac{d_{\text{SDDI}}}{\sigma_{(P-E_P)}}
\]  

[1.5]

where \(\sigma_{(P-E_P)}\) is the standard deviation of (P – EP) for the control run. SDDI is defined in terms of the SDDI for the previous month and the SDDI moisture anomaly index, similar to the PDSI formulation.

\[
SDDI(i) = 0.897SDDI(i-1) + Z_{\text{SDDI}}(i)
\]  

[1.6]

In cases where the standard deviation (\(\sigma_{(P-E_P)}\)) equaled zero, SDDI was set to a skip value.

SDDI results from high latitudes should be considered with caution due to the limitations of the Thornthwaite potential evapotranspiration equation with freezing temperatures. In freezing conditions, soil moisture and groundwater are not available for evaporation and precipitation runs off more easily so calculations of changes in precipitation and evapotranspiration may not be relevant.
Past, Present and Future Drought Index Values

SDDI and PDSI values are highly correlated in North America [Rind et al., 1990]. Using both drought indices in the 20th and 21st centuries in addition to PDSI calculated from tree rings dating back 2000 years, we can construct a long-term timeseries of drought conditions. Tree ring reconstructions of North American PDSI values over the last 2000 years show a series of mega droughts in the Southwestern U.S. [Cook et al., 2004]. It should be noted that there is a possibility of longer-term variability of drought occurrence than is seen in the tree ring data, where a linear growth trend is factored out as an assumption in the data.

The percent of gridboxes experiencing drought equal or more severe than at the 5% level with time over the last 2000 years in North America is shown in Figure 1.5. Both Figure 1.5 and 1.6 include 20th century monthly surface air temperatures and precipitation from the CRU TS 2.0, 0.5-degree global 1901-2000 time series dataset [Mitchell and Jones, 2005] and 20th and 21st century GCM averages.

Model SDDI projections show drought conditions in the next 100 years far exceeding historical mega drought extent and duration in North America. This trend is not only in North America; it extends to conditions around the world. In Figure 1.7, the percentage of gridboxes experiencing 5% drought or worse increases at a rapid pace over the 21st century in all five GCMs according to both water availability measures. Globally averaged SDDI calculated from observed surface air temperature and precipitation also agrees with the GCM SDDI over the course of the 20th century (Figure 1.7). 21st century projections are discussed in more depth in Chapter 2.
1.4 Potential Evapotranspiration

An essential component of drought index calculations is the potential evapotranspiration (EP). EP is also important in GCM evaporation calculations. Evapotranspiration describes the amount of moisture moved from the land to the atmosphere through evaporation and vegetative transpiration. Potential evapotranspiration (EP) is the evapotranspiration from a thoroughly wet surface. Over a wet surface, such as a lake, evapotranspiration should roughly equal potential evapotranspiration.

1.4.1 Various Formulations

There are many ways to calculate EP from meteorological inputs. The differences between these methods should not be taken for granted given that they are, in some cases, an order of magnitude apart from one another. In this section, nine EP methods are discussed and finally compared at the end of the section.

*Thornthwaite Method*

PDSI and SDDI use the Thornthwaite method to calculate potential evapotranspiration. To calculate Thornthwaite EP, first derive the monthly (i) and annual (I) heat indices for each grid box.

\[
i = \left( \frac{T_{mo}}{5} \right)^{1.514} \quad [1.7]
\]

\[
I = \sum_{i}^{12} i \quad [1.8]
\]

where \(T_{mo}\) (in °C) is the average temperature for the month. A multi-year calculation has only 12 monthly heat index values, one for each calendar month. The first equation can only be used
for non-freezing conditions due to the non-integer exponent. In cases where the monthly average
temperature falls below 0°C, the monthly heat index \( i \) is set to zero. The sum of the monthly
heat indices gives the annual heat index. The unadjusted potential evapotranspiration \( (E_P) \) can be
calculated with the following equation

\[
\text{unadjusted } E_P = 1.6 \left( \frac{10T}{I} \right)^m
\]  

[1.9]

Where \( T \) (in °C) is the monthly temperature value and \( m \) is defined as

\[
m = (6.75 \times 10^{-7})I^3 - (7.71 \times 10^{-5})I^2 + (1.79 \times 10^{-2}) + 0.492
\]  

[1.10]

To avoid division by zero, in situations where the annual heat index \( I \) equals zero, the ratio
of temperature \( T \) to the annual heat index is set to unity. The unadjusted \( E_P \) is set to the
minimum value of zero when the temperature \( T \) is less than 0°C again due to imaginary values
arising from the non-integer exponent. Unadjusted \( E_P \) values are adjusted for day length using
coefficients found by Thornthwaite [1948]. For \( T \) values above 80°F, \( E_P \) only depends on \( T \), not \( I \)
or \( m \). \( E_P \) values for temperatures higher than 80°F (26.5°C) are assigned from Figure 13 by
Thornthwaite [1948].

The dependence of the Thornthwaite potential evapotranspiration on temperature alone is
unlike other methods, which use other variables as well, such as incident radiation and humidity.
This is a disadvantage for the Thornthwaite method since a decrease in incident radiation from
aerosol pollution or an increase in relative humidity could decrease evaporation rates, even
during periods of warming. Changes in cloud cover could create the same obstacle. Observations
of open pans of water have shown decreasing rates of evaporation over several recent decades
likely for these reasons [Roderick and Farquhar, 2002]. This limitation must be kept in mind
when using the Thornthwaite method.
Aerodynamic Method

The potential evapotranspiration ($E_p$) used in the GISS, CCCma, HadCM3, GFDL and MIROC land surface schemes are parameterized using the bulk aerodynamic formulation

$$E_p = \rho V_s C_q (q_g - q_s) = C_A (q_g - q_s)$$  \[1.11\]

where $\rho$ is the density of air, $V_s$ is surface wind speed, $C_q$ is the turbulent transfer coefficient, $q_g$ and $q_s$ are the ground surface and surface air specific humidities respectively, and $C_A$ is the atmospheric conductance [Rosenzweig and Abramopolous, 1997; Rind et al., 1997; Verseghy et al., 1993; Cox et al., 1999; Milly and Shmakin, 2002; Takata et al., 2003]. The ground surface specific humidity is assumed to be at the saturation value.

$$q_g = 0.622 \frac{e_{sat}(T_g)}{P_g}$$  \[1.12\]

where $e_{sat}(T_g)$ is the saturation vapor pressure at the surface and $P_g$ is the ground surface air pressure. Temperatures are lower over wet surfaces due to the energy used by evaporation. Using the saturation value at ground surface temperature leads to overestimation of the actual ground-level specific humidity over many land regions. Over well-watered vegetation the evapotranspiration has been shown to be close to evaporation over open water (potential evapotranspiration) in the same conditions. A possible explanation is that the stomatal resistance to water loss is compensated by larger roughness values, which lead to larger transfer coefficients [Brutsaert, 2005]. However, since the evaporation is generally much less than the potential value, an efficiency factor ($\beta$)

$$\beta = \frac{C_S}{C_A + C_S}$$  \[1.13\]

is used for scaling, which ranges from 0 to 1, where $C_S$ is the surface conductance (either bare soil or canopy) in the GISS GCM. CCCma, HadCM3, GFDL and MIROC also make use of
surface and canopy conductance to scale the aerodynamic potential evapotranspiration in similar ways [Verseghy et al., 1993; Cox et al., 1999; Milly and Shmakin, 2002; Takata et al., 2003]. GISS GCM evaporation (E) is then calculated using

$$E = \beta E_p$$ \hspace{1cm} [1.14]

$\beta$ is maximum in well-watered conditions and minimum when the soil/vegetation is driest. The $\beta$ factor is generally very low in models to compensate for large aerodynamic potential evapotranspiration values.

Other Potential Evapotranspiration Methods

"Full" Penman-Monteith Method

\[
E_p = \frac{\Delta (R_n - G) + K_{\text{time}} \rho_a c_p \frac{e_s - e_a}{r_a}}{\Delta + \gamma (1 + \frac{r_s}{r_a})} / \lambda
\]

where

- $E_p$ is the potential evapotranspiration (mm d$^{-1}$)
- $R_n$ is the net radiation (MJ m$^{-2}$ d$^{-1}$)
- $G$ is the soil heat flux (MJ m$^{-2}$ d$^{-1}$)
- $(e_s - e_a)$ represents the vapor pressure deficit of the air (kPa)
- $e_s$ is saturation vapor pressure of the air (kPa)
- $e_a$ is the actual vapor pressure of the air (kPa)
- $\rho_a$ is the mean air density at constant pressure (kg m$^{-3}$)
- $c_p$ is the specific heat of the air (MJ kg$^{-1}$ °C$^{-1}$)
- $\Delta$ is the slope of the saturation vapor pressure temperature relationship (kPa °C$^{-1}$)
- $\gamma$ is the psychrometric constant (kPa °C$^{-1}$)
\( r_s \) is the (bulk) surface resistance (s m\(^{-1}\))

\( r_a \) is the aerodynamic resistance (s m\(^{-1}\))

\( \lambda \) is latent heat of vaporization (MJ kg\(^{-1}\))

\( K_{\text{time}} \) is a unit conversion, equal to 86,400 s d\(^{-1}\) for ET in mm d\(^{-1}\)

**FAO-56 Penman-Monteith Method**

\[
E_P = \frac{0.408 \Delta (R_n - G) + \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_2)}
\]

where

\( T \) is the mean daily air temperature at 2m height (°C)

\( u_2 \) is the wind speed at 2m height (m s\(^{-1}\))

**Penman [1948] Method**

\[
E_P = \frac{\Delta (R_n - G) + K_w \frac{\gamma}{\lambda} (a_w + b_w u_2) (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_2)}
\]

where

\( K_w \) is a unit constant, equal to 6.43 for \( ET_0 \) in mm d\(^{-1}\)

\( a_w \) and \( b_w \) are wind function coefficients that often receive regional calibration. They were originally 1.0 and 0.537 m s\(^{-1}\) respectively

**Hargreaves Method**

\[
E_P = 0.0023 (T_{\text{max}} - T_{\text{min}})^{0.5} (T_{\text{mean}} + 17.8) R_a
\]

where
$T_{\text{max}}$ is the maximum daily air temperature ($^\circ\text{C}$)

$T_{\text{min}}$ is the minimum daily air temperature ($^\circ\text{C}$)

$T_{\text{mean}}$ is the mean daily air temperature ($^\circ\text{C}$)

$R_a$ is the TOA shortwave radiation (mm d$^{-1}$)

**Priestly-Taylor Method**

$$E_p = 1.26 \frac{\Delta}{\Delta + \gamma} \frac{R_a - G}{\lambda} \quad [1.19]$$

**Makkink Method**

$$E_p = 0.61 \frac{\Delta}{\Delta + \gamma} \frac{R_s}{2.45} - 0.12 \quad [1.20]$$

where

$R_s$ is the surface shortwave radiation (MJ m$^{-2}$ d$^{-1}$)

**Turc Method**

$$E_p = a_T 0.013 \frac{T_{\text{mean}}}{T_{\text{mean}} + 15} \frac{23.8856R_s + 50}{\lambda} \quad [1.21]$$

where

$$a_T = \begin{cases} 1, & RH_{\text{mean}} \geq 50\% \\ 1 + \frac{50 - RH_{\text{mean}}}{70}, & RH_{\text{mean}} < 50\% \end{cases} \quad [1.22]$$

1.4.2 Potential Evapotranspiration Comparisons

**Local Comparison**
The potential evapotranspiration methods described above were used to compare \( E_P \) values in Rochester, New York calculated with inputs from observations (weather station data) and a GCM (GISS Model ER). Figure 1.8 displays the timeline of \( E_P \) calculated from local weather station data between 1961 and 1990. The different \( E_P \) methods show similar interannual variability but staggering absolute values ranging from 1.5 to 3.5 mm/day. The FAO 24 Corrected Penman and Turc methods show the most and least aggressive \( E_P \) values respectively.

Figure 1.8 shows all months between 1961 and 1990, the \( JJA \) mean \( E_P \) in New York is ranges from 3.44 to 6.07 mm/day for the Makkink \( E_P \) and FAO 24 Corrected Penman \( E_P \) respectively (Table 1.4). The \( JJA \) mean pan evaporation measured in Rochester, New York in 1981 was approximately 5.32 mm/day, which is in the same range as the \( E_P \) values but close to the high end [WWCB, 1981].

Figure 1.9 shows the various \( E_P \) calculations using meteorological input from the IPCC AR4 “Climate of the 20\textsuperscript{th} Century” run of the GISS GCM for the gridbox containing Rochester. The \( E_P \) values from the weather station data are a similar magnitude although larger than the \( E_P \) calculations using GISS data. Overall, in Figure 1.8, even for well-established \( E_P \) calculations (not including Aerodynamic \( E_P \)), the largest and smallest values are more than a factor of two off from one another. In Figure 1.9, we see that by using the GISS model ER data, there is also a factor of two difference in \( E_P \) (not including Thornthwaite \( E_P \)). In Figure 1.9, the values range between 1 and 3 mm/day with the same lower bound (Turc, not including Thornthwaite) as in Figure 1.8. Table 1.4 lists the JJA averages, which range from 4.09 to 5.59 mm/day. This range compares favorably with the pan evaporation average in Rochester. In both the GCM and weather station calculations, \( E_P \) values do not show a noticeable trend between 1961 and 2000.
However, it can be said that there is much less uniformity and variability from year-to-year in the GCM-derived $E_P$.

The changes in Thornthwaite, Penman-Monteith, Hargreaves-Semani, Priestly-Taylor and Turc $E_P$ between 2080 to 2089 and 1970 to 1999 for MIROC, GFDL and GISS over New York are shown in Figure 1.10 [courtesy of Richard Goldberg, 2010]. The SDDI and PDSI were then calculated using these five $E_P$ methods (Figure 1.10) [courtesy of Richard Goldberg]. In this region, Hargreaves, Priestly-Taylor and Turc $E_P$ show the least sensitivity to global warming, which produces SDDI and PDSI changes that are less severe and consequently, more similar to soil moisture projections. However, this does not necessarily mean they do a better job; there is no evidence that reduced sensitivity schemes do a better job matching observations of pan evaporation than increased sensitivity schemes (i.e. Thornthwaite and Penman-Monteith). In addition, it should be noted that PDSI drying projections are more severe in this case than SDDI and the different $E_P$ methods have the same relative effects on PDSI and SDDI.

Global Comparison

Timelines of global land-only average Aerodynamic, Thornthwaite, Hargreaves and Penman $E_P$ are shown together for the period 1901 to 2100 calculated using inputs from the GISS GCM in Figure 1.11. Aerodynamic $E_P$ stands out as being an order of magnitude larger than any of the other $E_P$ values and having significant seasonal variability. It can also be clearly seen that the Aerodynamic $E_P$ increases in the 21st century. Thornthwaite $E_P$ values are the smallest but like the other $E_P$ values, are also increasing with time.

The impact of these four very different $E_P$ methods on SDDI is shown in Figure 1.12. In Figure 1.12, the global average land-only values are shown for SDDI calculated with
Aerodynamic, Thornthwaite, Hargreaves and Penman $E_P$ using necessary meteorological input from the GISS Model ER (IPCC AR4 Climate of the 20th Century and A2 scenario). The most severe SDDI projections are for the SDDI calculated using the largest $E_P$, Aerodynamic $E_P$. Thornthwaite SDDI is second in severity to the Aerodynamic SDDI by 2100. The Hargreaves SDDI is the least severe by 2100. The trends of Thornthwaite and Penman SDDI values with time are very similar despite their differences in the absolute value of $E_P$, as shown in Figure 1.11. Penman $E_P$ as shown in Figure 1.8 and 1.9 is close enough to be considered representative of the other $E_P$ values. This implies that all the $E_P$ formulations would likely produce fairly similar SDDI values with the exception of the more extreme changes from the Aerodynamic $E_P$. SDDI does not necessarily follow the $E_P$ magnitudes because of the normalization due to the use of its standard deviation (Equation 1.5).

Hargreaves could only be calculated in the periods: 1961-2000, 2046-2065 and 2081-2100 due to $T_{\text{max}}$ and $T_{\text{min}}$ data availability. To deal with the gaps in the Hargreaves $E_P$, 3 methods were used to resume calculating SDDI. In the first Hargreaves method, SDDI is reset to zero after each break in data. In the second Hargreaves method, SDDI resumes with the last available SDDI value. Finally, in the third Hargreaves method, a linear trend is calculated using the 24-month average at the beginning and end of the previous period to estimate the value of SDDI at the beginning of the next period. After the first 2.5 years of the 2046-2065 and 2081-2100 periods, all three of the Hargreaves methods are essentially the same (Figure 1.12).

1.5 Conclusions

20th century GCMs and LSMs disagree with each other and among themselves on global soil moisture due to varying definitions. GCMs have the largest disconnect with the MIROC model claiming 24 times the global average soil moisture as GFDL. Both LSMs and GCMs with the
exception of CCCma agree that soil moisture is decreasing (Figures 1.1 and 1.3). LSMs show a much steeper decline indicating that GCMs could perhaps be underestimating drought.

According to tree ring data and reconstructed PDSI values, North America has a history of mega-droughts [Cook et al., 2004]. GCM projections show conditions rivaling these historic droughts. Global projections of the spread of drought extent show agreement between GCM projections and SDDI calculated with observations in the 20th century. The spread of drought extent is serious for both soil moisture and SDDI projections. Soil moisture changes indicate that 5% drought conditions will increase from covering approximately 3% of land gridboxes to an average of around 20% for all GCMs by the end of the century. SDDI projections are more extreme with severe drought (5% or worse) reaching up to 45% of land gridboxes by the year 2100.

However, SDDI is dependent on $E_p$ calculations, which can be orders of magnitude apart. A local comparison of $E_p$ calculated from meteorological observations and GCM data in Rochester, New York showed an overlapping distribution of $E_p$ values that agreed with pan evaporation measurements. However, when the various $E_p$ methods are used to calculate SDDI, we find that SDDI shows a remarkable resilience to the different magnitudes of $E_p$ due to the use of its standard deviation in the SDDI formulation.

Given a single water availability measure (soil moisture or SDDI), we see a range of predicted values between models, but this inter-measure variability pales in comparison to the far more striking discrepancy that asserts itself when we contrast the future projections of the two measures. Understanding the distinctions between models is important, and we will strive to do this in Chapter 2, but if we truly wish to understand the future of water availability in the next
century, we must also resolve the larger discrepancy between water availability measures, which we will examine in Chapter 3.
2 Future Global Water Availability

2.1 Introduction

Chapter 1 explored some of the fundamental differences between soil moisture and SDDI. Both water availability measures present unique perspectives and challenges. The lack of global long-term high-resolution root-zone soil moisture measurements was discussed as an obstacle for calibrating GCM soil moisture output. A number of LSMs driven with observed meteorological inputs come closest to filling this need for data until the SMAP satellite retrievals become available (scheduled to launch in 2013). However, as stated in Chapter 1, LSMs and GCMs do not agree with each other or among themselves on soil moisture. Unlike soil moisture, SDDI can be easily calculated globally and historically using observed surface temperature and precipitation. Any challenges that arise from using SDDI are generally due to its sensitivity to the variables in its formulation, which can be as few as two or many more depending on the choice in potential evapotranspiration ($E_p$) method.

While much of Chapter 1 was devoted to the mathematical mechanics and measurement challenges of evaluating water conditions, Chapter 2 explores the characteristics of individual GCMs and the atmospheric variables that drive water availability projections. Our goal is to form a solid picture of the abilities of each model in addition to presenting their 20th and 21st century projections. By the end of this chapter we should be able to discuss whether using different models increases or decreases the consensus between soil moisture and SDDI. Is the uncertainty in future water availability primarily due to the measures or the models?
2.2 Selection of Models

Five GCMs were used as a representative sampling of the twenty-three IPCC AR4 models. Table 2.1 gives an overview of each model. All five models are well established in the modeling community and the host institutions are globally representative. Only two of the three U.S. models are in the study, GISS and GFDL to avoid commonality among the models. The other U.S. model, NCAR uses the same Lin-Rood finite volume dynamics core as GFDL and the same deep convection scheme as another model in the study, CCCma [CMIP3 Climate Model Documentation, 2011].

The five chosen models span the spectrum of AR4 resolutions and equilibrium climate sensitivities. In this study, GFDL represents the highest resolution at 2.0×2.5 (NCAR is the AR4 model with the highest resolution at 1.4×1.4) while GISS (4×5) has the lowest in this study and among AR4 models. The full range of equilibrium climate sensitivities among AR4 models is 2.1°C to 4.4°C. The models used in this study show increased mean surface temperatures between 2.7°C and 4°C in the GISS and MIROC models respectively in response to doubled CO₂. The chosen models are thus representative in a broad sense of the range in global warming estimates.

GCMs were also chosen based on the availability of IPCC A2 run variables necessary for analysis. In addition, the models chosen represent various atmospheric forcing scenarios (i.e. stratospheric ozone and black carbon) and skill in simulating El Niño-Southern Oscillation (ENSO) interdecadal variability [Lin, 2007]. Table 2.2 lists the forcing agents for each model. They all have greenhouse gas (CO₂, CH₄, N₂O, tropospheric O₃ and CFC’s) and SO₄ forcing. However, two of the five GCMs (CCCma and HadCM3) do not include black carbon forcing (Table 2.2). Three of the five have recovering stratospheric ozone in the 21st century (GISS,
GFDL, HADCM3) while the CCCma model maintains a constant seasonal cycle and the MIROC model does not take stratospheric ozone into account at all, which partially accounts for the range in the Southern Annular Mode (SAM) responses. All five models are projecting increases in the SAM index and Northern Annular Mode (NAM) index although they disagree on magnitude [Miller et al., 2006]. For the full range of AR4 models, there are some that do not show increases in NAM.

There is also a spread in ENSO-like variability among the five models in this study. Lin [2007] found HadCM3 has an oscillation shorter than the observed ENSO period while CCCma, GISS and MIROC show oscillations at periods longer than six years. GFDL is the one model out of these five that is able to produce the interdecadal variability of ENSO. A study by AchutaRao and Sperber [2006] shows that this group of models also represents a range in ENSO amplitude. GISS has a small ENSO amplitude while HadCM3 and GFDL are much larger and more realistic. At this time there is no consensus in projections of 21st century ENSO amplitude or frequency. In the 21st century, three models display an El Niño-like base state change in average tropical Pacific SSTs and a decrease in variability: CCCma, GFDL and MIROC [IPCC, 2007]. One model, HadCM3 displays a La Niña-like base state change and increased variability. While GISS was not evaluated in the IPCC [2007] study, as mentioned above, it is unable to produce a realistic 20th century amplitude or oscillation [AchutaRao and Sperber, 2006; Lin, 2007]. In some cases, decreased variability may be outweighed by large shifts in base states. SSTs in the tropical eastern Pacific increase by over 1.8°C in all five models and over 2.4°C in all but GFDL and GISS.

This subset of five AR4 GCMs is representative of the larger IPCC AR4 group in terms of spatial resolution, climate sensitivity, atmospheric forcing and ENSO interdecadal variability and
2.3 GCM Background and Characteristics

Coupled GCMs represent the effects of many individual model components, which work independently and as a team at various points in the simulations. Since each component of the system has its individual tendencies, strengths and limitations, a collection of these components forms its own unique characteristics and biases. The models are influenced by the individual schemes or by communication or lack of communication between the components. This section provides an overview of each model and its behavior and biases. The 20th and 21st century IPCC projections are discussed for each model in terms of surface air temperature, precipitation, SDDI and soil moisture.

The 20th century simulations are from the IPCC Climate of the 20th Century (20C3M) experiments. The 21st century projections use the IPCC Special Report on Emissions Scenarios (SRES) A2 scenario. The SRES A2 storyline is characterized by a heterogeneous world with regionally oriented economic development and a continuously increasing population [Nakicenovic et al., 2000]. The A2 scenario has some of the most aggressive climate forcing agents. By the year 2100, annual global CO₂ emissions for the A2 scenario are second only to the A1F1 scenario and A2 has the highest global methane emissions [Nakicenovic et al., 2000].

As discussed in the previous section, there are many differences between the forcing agents used in each model, particularly the handling of black and organic carbon, aerosol indirect effects, dust, sea salt and land use. The forcing agents used by each model for the 20C3M and SRES A2 experiments are listed in Table 2.2. Although the model data presented in this section is from the same 20th and 21st century IPCC runs, each model has different cloud, land, convection, boundary layer, and radiation schemes. They also have differing assumptions about
forcing agents beyond what is prescribed by IPCC.

2.3.1 Canadian Centre for Climate Modelling and Analysis Coupled Model

The Canadian Centre for Climate Modelling and Analysis (CCCma) third generation Coupled Global Climate Model (CGCM3.1) version T47 uses the third generation Atmospheric GCM (AGCM3, \(\sim 2.8^\circ \times 2.8^\circ\) with 31 layers) [McFarlane et al., 2005; Scinocca et al., 2008] and the same ocean component from the previous generation coupled model, CGCM2 (1.9°×1.9° with 29 layers and a rigid lid) [McFarlane et al., 1992]. A new addition to the CGCM3.1 is the Canadian Land Surface Scheme (CLASS) [Verseghy et al., 1993], which includes three soil layers, a snow layer where applicable, and a vegetative canopy treatment. It should be noted that CCCma CGCM3.1 is the only model in this study that is flux corrected. The equilibrium climate sensitivity is 3.4°C and the transient climate response is 1.9°C.

CCCma has been shown to produce slightly wetter and warmer conditions over land in JJA than observations [Verseghy et al., 1993]. Most notably, JJA modeled temperatures over Greenland, southwestern United States, northeastern Africa and the Middle East to northern India were found to be significantly warmer than observed values. The same regions experience negative temperature anomalies in DJF. Verseghy et al. [1993] attributed these discrepancies to incomplete data on the morphological characteristics of the vegetation in those regions, particularly the desert and semi-desert regions. The positive temperature anomalies in Central Asia were linked to negative sea level pressure anomalies in the northern hemisphere and were potentially caused by flaws in the stomatal resistance formulation used.

In DJF, CCCma produces slightly cooler and wetter conditions over land than observations [Verseghy et al., 1993]. The strongest negative temperature anomaly is in Southern Asia. There are also regions associated with large positive temperature anomalies in DJF such as central
Asia, eastern Siberia and northwestern Canada. Northwestern Canada and eastern Siberia are covered in boreal forests. Verseghy et al. [1993] assert that the use of canopy parameter measurements from coniferous trees in temperate forests as opposed to boreal forests is the problem since coniferous trees in temperate forests are taller and denser and would incorrectly decrease albedo by covering too much underlying snow.

2.3.1.1 20th Century

The IPCC AR4 Climate of the 20th Century experiment (20C3M) was used for the years 1901 to 2000. The initial state is taken from the preindustrial control (Plcntl) experiment. Time-varying forcings include CO₂, CH₄, N₂O, CFC’s, SO₄, dust, volcanic aerosols, sea salt, stratospheric and tropospheric O₃. Land use and solar forcings also vary over the 20th century [IPCC, 2007]. There are no aerosol indirect effects included.

Figure 2.1 shows the 20th century zonal observed and modeled surface air temperature annual anomalies from the 1928-1978 average. CCCma displays strong warming at all latitudes in the latter quarter of the 20th century. Between 1901 and ~1975, the high northern latitudes have stronger negative anomalies than seen in observations. After 1975, the temperature anomalies in the high northern latitudes are strongly positive compared to observations. Figure 2.2 is the globally averaged, land-only surface air temperature timeline from 1901 to 2100. The temperature is displayed as an anomaly from the 1971-2000 mean. In the first half of the 20th century, CCCma shows global land temperatures >0.5°C below observed anomalies not because the early 20th century had cooler temperatures but because the reference period 1970-2000 was much warmer than observations.

Figure 2.3 shows the 20th century zonal modeled and observed precipitation annual anomalies from the 1928-1978 averages. CCCma shows very little variability compared to the observations.
and the variability in CCCma is confined to a narrow band around the equator. In the observations the variability is more spread out through the tropics and subtropics. In the last 20 to 30 years of the 20th century, CCCma displays increased precipitation in the mid and high latitudes that is stronger than the observed northern increase. This discrepancy between CCCma and observations does not appear in the global mean land-only area-weighted precipitation in Figure 2.2 although it is consistent with the rapid increased warming at high latitudes. Figure 2.2 shows CCCma in agreement with observations on the magnitude of precipitation. However, Figure 2.2 also highlights the lack of variability in CCCma precipitation compared to observations. The lack of realistic variability may be explained by ENSO. Lin [2007] showed that CCCma has an ENSO period longer than six years that is too long compared to observations.

The global mean land-only SDDI from 1901 to 2100 is displayed in Figure 2.4. The SDDI values were calculated using modeled and observed temperature and precipitation. Negative SDDI indicates drier conditions. CCCma has a more positive mean SDDI than observations until around 1961, around the time temperatures rapidly increased in CCCma. After 1961, CCCma becomes drier than observations.

Figure 2.4 also shows the global mean soil moisture timeline from 1901 to 2100 as anomalies from the 1971-2000 averages divided by the 1971-2000 standard deviation. CCCma soil moisture in the 20th century appears to be steady. In Chapter 1, Figure 1.2 shows the global mean soil moisture values. CCCma has global mean soil moisture staying fairly steady with average values around 435 kg/m^2. This is lower than the soil moisture in the four LSMs discussed in Chapter 1, which ranged from 500 to 800 kg/m^2 between 1979 and 2009 (Figure 1.1).

2.3.1.2 21st Century

The IPCC AR4 SRES A2 was used for the years 2001 to 2100. The initial state was taken from
the 20C3M experiment. Time-varying forcing agents for SRES A2 include CO₂, CH₄, N₂O, CFC’s and SO₄. Solar forcing, land use, stratospheric and tropospheric O₃, dust, volcanic aerosols and sea salt are set to constant or annually cyclic distribution for the 21st century [IPCC, 2007]. There are no indirect aerosol effects included in this model.

Figure 2.5 is a rescaled and extended version of Figure 2.1. It is the zonal 20th century observed and 20th and 21st century modeled surface air temperature annual anomalies from the 1928-1978 average. The global warming signature becomes clear in this figure. CCCma continues to show strong warming at all latitudes, particularly at high northern latitudes. Changes in the seasonal zonal mean surface air temperature from the last thirty years of the 20th century to the last thirty years of the 21st century are shown in Figure 2.6. In JJA, CCCma temperatures rose at all latitudes with peaks at 80S, 20S and 40N. In DJF, temperatures also increased at all latitudes. The largest increase is in the high northern latitudes.

20th and 21st century precipitation anomalies are displayed in Figure 2.7. CCCma has three pronounced bands of precipitation increase: 15N to 15S, 40N to 90N and 45S to 90S. Decreased precipitation is found in two bands: 15S to 45S and 15N to 40N. These zonal patterns strengthen over the course of the 21st century. The pattern also shows up in the JJA and DJF land-only zonal mean precipitation difference between the end of the 20th and 21st centuries (Figure 2.6). The poles and tropics show increase in both seasons. Southern mid latitude decreases occur in DJF.

CCCma soil moisture by the end of the 21st century appears to be increasing slightly (Figure 2.4). In Chapter 1, Figure 1.2 shows that CCCma has global mean soil moisture staying fairly steady with a small increase through the 21st century up to an average value of approximately 440 kg/m². The increase in soil moisture is not enough to fall into the range of the four LSMs discussed in Chapter 1, which ranged from 500 to 800 kg/m² between 1979 and 2009 (Figure
1.1). Figure 2.9 shows the zonal soil moisture anomalies as they progress through the 20th and 21st centuries. Soil moisture decreases are focused in three bands: 15N to 20N, 35S to 45S and 75N to 80N. There is also a wetter trend between 45N and 70N. The 15N to 20N band and the 35S to 45S band correspond to increased downwelling in CCCma in Figure 2.10.

The SDDI trend over the 20th and 21st centuries is shown in Figure 2.4. CCCma exhibits a steady decline over time. The JJA and DJF zonal change in SDDI for CCCma show decreases (drying) all latitudes between 60S and 50N with increases at high latitudes (Figure 2.8). The evolution of zonal land-only SDDI changes can be more clearly seen in Figure 2.9. In Figure 2.9, CCCma shows three drying bands: between 15N and 40N, 15S and 30S, and 40S to 55S.

The 15N to 40N band partially corresponds with downwelling in the JJA and DJF 1901 to 2100 zonal mean vertical velocity anomalies in Figure 2.10 where vertical velocity is defined as the 200mb to 800mb average of $\frac{\partial p}{\partial t}$. Zonally, CCCma displays an enhanced JJA Hadley circulation in both hemispheres and an enhanced Ferrell circulation in the southern hemisphere. In DJF, there is mainly enhanced Hadley circulation in the downwelling branch in the southern hemisphere and upwelling in the southern Ferrell circulation.

SDDI and soil moisture have varying sensitivities to temperature and precipitation in different parts of the globe. Figure 2.11 shows the time series correlations between SDDI and surface air temperature, SDDI and precipitation, soil moisture and surface air temperature, and soil moisture and precipitation for each gridbox. CCCma shows mild positive correlation between surface air temperature over land and SDDI at high southern and northern latitudes and eastern Asia. With increased temperature, wetter conditions would be expected. The opposite is true over the tropics, subtropics and midlatitudes (with the exception of eastern Asia) where temperature and SDDI are negatively correlated. Increased temperatures lead to increased evaporation and drier
conditions. Precipitation and SDDI are positively correlated across the globe for CCCma particularly in eastern China, Antarctica and northern North America, areas where temperature shows only a mild influence.

The strongest negative correlations between soil moisture and surface air temperature in CCCma occur over northern Africa, southern Europe, and the southwestern U.S. while most of the globe shows only weak correlations. In these areas, as temperatures rise, soil moisture noticeably decreases. Soil moisture is positively correlated with precipitation globally but particularly in Australia and central North America for CCCma.

2.3.2 Geophysical Fluid Dynamics Laboratory Coupled Model

The Geophysical Fluid Dynamics Laboratory (GFDL) Coupled Model 2.1 (CM2.1) uses the atmosphere and land components referred to as AM2.1 (2.0° × 2.5° with 24 layers) and LM2.1 (0.3°-1.0°×1.0° with free surface) [Anderson et al., 2004; Delworth et al., 2006]. LM2.1 is based on the Land Dynamics (LaD) model [Milly and Shmakin, 2002] and the ocean model, OM3.1 is based on the Modular Ocean Model code (MOM4) [Gnanadesikan et al., 2006; Griffies et al., 2003]. The equilibrium climate sensitivity of GFDL CM2.1 is 3.4°C and the transient climate response is 1.5°C. In this model the direct effects of organic and black carbon, dust, sulfate, and sea salt are accounted for. However, indirect aerosol effects were not included.

GFDL CM2.1 has a tropospheric cold bias [Delworth et al., 2006]. There is too little warming in the higher latitudes and too much warming in the Tropics [Knutsen et al., 2006]. The cold bias has been lessened (but is still present) in the high latitudes by altering the land model so evaporation is suppressed when the soil is frozen at a depth of 30 cm [Delworth et al., 2006]. This reduces evaporation and cloudiness and increases surface shortwave radiation and surface air temperature. However, the increased surface temperatures act to melt Arctic sea ice, which is
already too thin when compared to observations.

Regionally, the GCM has difficulty with a number of areas, specifically northern Asia, Canada, and the southern Indian Ocean where warming is too weak and the southeastern United States where warming is too strong. In northern Asia, there is also a problem with unrealistic seasonality of warming, which is attributed to the lack of a positive trend in the model’s 20th century Arctic Oscillation [Knutsen et al., 2006]. It is thought that in some regions such as the southeastern United States and southern Asia that the inclusion of indirect aerosol forcing (currently not included) would lead to smaller differences between modeled temperature and observations. Standard deviations in SSTs and surface air temperatures from the GFDL CM2.1 show a tendency for excessive variability over many land and ocean regions when compared to observed standard deviations in temperature particularly in the equatorial Pacific, over land in northern hemisphere high latitudes, and in the central southern United States [Delworth et al., 2006]. In the GCM, ENSO variability occurs too far west from the South American coast when compared to observations. The SLP anomalies associated with other modes of variability such as the Northern and Southern Annular Modes (NAM and SAM) can be realistically simulated with the GFDL CM2.1 [Delworth et al., 2006].

In general, GFDL CM2.1 tends to produce wetter conditions than observations over land. Delworth et al. [2006] found that GFDL CM2.1 overestimates observed annual mean precipitation in the southern half of Africa, central Asia, Europe, North America, and the western coast of South America while underestimating observed precipitation in the rest of South America including the Amazon Basin. Also, the modeled precipitation shows a doubled intertropical convergence zone (ITCZ).
2.3.2.1 20th Century

The IPCC AR4 Climate of the 20th Century experiment (20C3M) was used for the years 1901 to 2000. The initial state is taken from the preindustrial control (PIcntrl) experiment. Forcings include time-varying CO₂, CH₄, N₂O, halons, tropospheric and stratospheric O₃, anthropogenic tropospheric sulfates, black and organic carbon, volcanoes, land use and solar forcing [CMIP3 Climate Model Documentation, 2011; IPCC, 2007]. This simulation does not include aerosol indirect effects.

Figure 2.1 shows the 20th century zonal observed and modeled surface air temperature annual anomalies from the 1928-1978 average. GFDL displays strong warming in the tropics, subtropics and high latitudes in the final decade of the 20th century. Between 1901 and ~1985, the high northern latitudes and equator have stronger negative anomalies than seen in observations. After 1985, the temperature anomalies are of a similar magnitude to the observations. However, the observations do not show minimum warming in the mid latitudes as seen in GFDL.

Figure 2.2 is the globally averaged, land-only surface air temperature timeline from 1901 to 2100. The temperature is displayed as an anomaly from the 1971-2000 mean. In the 20th century, GFDL shows global land temperatures slightly below observations until around 1925. In the 1980s and 1990s, GFDL shows larger variability than observations.

Figure 2.3 shows the 20th century zonal modeled and observed precipitation annual anomalies from the 1928-1978 averages. GFDL shows very strong variability in the tropics compared to the observations. In the observations the variability is more spread out through the tropics and subtropics. However, Lin [2007] found that GFDL is one of the only IPCC AR4 models that is able to capture the interdecadal variability of ENSO. AchutaRao and Sperber [2006] showed that GFDL has a more realistic ENSO amplitude than many other models. GFDL precipitation
anomalies do not display any discernable trend in the latter portion of the 20th century. The global mean land-only precipitation in Figure 2.2 shows that GFDL is wetter and more variable than observations.

The global mean land-only SDDI from 1901 to 2100 is displayed in Figure 2.4. The SDDI values were calculated using modeled and observed temperature and precipitation. Negative SDDI indicates drier conditions. GFDL has a larger mean SDDI than observations until around 1961. After 1961, GFDL SDDI and observations remain close.

Figure 2.4 also shows the global mean soil moisture timeline from 1901 to 2100 as anomalies from the 1971-2000 averages divided by the 1971-2000 standard deviation. GFDL soil moisture in the 20th century appears to stay steady. In Chapter 1, Figure 1.2 shows that GFDL has global mean soil moisture with average values around 50 kg/m². This is an order of magnitude lower than the soil moisture in the four LSMs discussed in Chapter 1, which ranged from 500 to 800 kg/m² between 1979 and 2009 (Figure 1.1).

2.3.2.2 21st Century

The IPCC AR4 SRES A2 was used for the years 2001 to 2100. The initial state was taken from the 20C3M experiment. Time-varying forcing agents for SRES A2 include CO₂, CH₄, N₂O, halons, tropospheric and stratospheric O₃, anthropogenic tropospheric sulfates, black and organic carbon. Solar forcing, land use change, dust, sea salt and volcanic aerosols are held fixed or annually cyclic in the 21st century [CMIP3 Climate Model Documentation, 2011; IPCC, 2007]. This simulation does not include aerosol indirect effects.

Figure 2.5 is the zonal 20th century observed and 20th and 21st century modeled surface air temperature annual anomalies. GFDL shows strong warming at all latitudes, particularly at high northern latitudes. Minimum temperature increases occur around 60S. Changes in the seasonal
zonal mean surface air temperature are shown in Figure 2.6. In JJA, GFDL temperatures rose at all latitudes with peaks at 30S and 40N. In DJF, temperatures also increased at all latitudes. The largest increase is in the high northern latitudes.

20\textsuperscript{th} and 21\textsuperscript{st} century precipitation anomalies are displayed in Figure 2.7. GFDL has increased precipitation from 45N to 90N and from 45S to 70S. There are decreases centered on 30N and 30S. Both the increases and decreases tend to strengthen over the course of the 21\textsuperscript{st} century. The pattern also shows up in the JJA land-only zonal mean precipitation difference between the end of the 20\textsuperscript{th} and 21\textsuperscript{st} centuries (Figure 2.6). In DJF, most of the change in zonal land precipitation is in the southern hemisphere.

GFDL soil moisture by the end of the 21\textsuperscript{st} century appears to be decreasing slightly (Figure 2.4). In Chapter 1, Figure 1.2 shows that GFDL has global mean soil moisture that stays fairly steady between 1901 and 2100 with average values around 40 kg/m\textsuperscript{2}, far from the LSM global mean values in Chapter 1 (Figure 1.1). Figure 2.9 shows the zonal soil moisture anomalies as they progress through the 20\textsuperscript{th} and 21\textsuperscript{st} centuries. Soil moisture decreases are focused in two bands: 40N to 60N and 45S to 55S. There is also a wetter trend between 5N and 5S. The northern hemisphere mid latitude band partially corresponds with the increased downwelling in GFDL in Figure 2.10.

The SDDI trend over the 20\textsuperscript{th} and 21\textsuperscript{st} centuries is shown in Figure 2.4. GFDL exhibits a steady decline over time. The JJA and DJF zonal change in SDDI for GFDL show decreases (drying) all latitudes between 60S and 60N with increases at high northern latitudes (Figure 2.8). The evolution of zonal land-only SDDI changes can be more clearly seen in Figure 2.9. In Figure 2.9, GFDL shows two drying bands: between 15N and 45N and 15S and 40S.

The 15S to 40S band partially corresponds with downwelling in the JJA and DJF 1901 to
2100 zonal mean vertical velocity anomalies in Figure 2.10. Zonally, GFDL displays an enhanced southern hemisphere JJA and DJF Hadley circulation in the downwelling arm and Ferrell circulation in the upwelling arm. Downwelling is also strengthened in the northern hemisphere mid latitudes mainly during DJF but also in JJA.

GFDL shows mild positive correlation between surface air temperature over land and SDDI at high southern and northern latitudes (Figure 2.11). So with increased temperature, wetter conditions would be expected. The opposite is true over the tropics, subtropics and midlatitudes where temperature and SDDI are negatively correlated. Increased temperatures lead to increased evaporation and drier conditions. Weak negative correlations occur over eastern Asia and northern Canada. Precipitation and SDDI are positively correlated across the globe for GFDL particularly in eastern Siberia, Alaska, the Midwest U.S., northern Brazil, western Africa and southern Europe.

The strongest negative correlations between soil moisture and surface air temperature in GFDL occur over northern and southern Africa, southern Europe, South America, Australia and the U.S. In these areas, as temperatures rise, soil moisture noticeably decreases. Soil moisture is positively correlated with precipitation globally but particularly in southern Europe, northern Africa, the Middle East, central North America and Australia for GFDL.

2.3.3 NASA Goddard Institute for Space Studies Coupled Model

The NASA Goddard Institute for Space Studies Model ER (GISS ER) is a coupled GCM with a 4°×5° atmosphere component with 20 layers [Schmidt et al., 2006] and a free surface ocean component with 4°×5° resolution and 13 layers [Russell et al., 1995]. The land component is based on Friend and Kiang [2005]. Model ER had an equilibrium climate sensitivity of 2.7°C and a transient climate response of 1.5°C.
The GISS model faces some limitations [Schmidt et al., 2006; Hansen et al., 2005]. GISS surface air temperature shows a cold bias particularly in Europe due to land use change and excessive aerosols in the region. Warming is slightly higher than observations in the tropics and lower than observations in northern mid and high latitudes. Also, volcanic events tend to result in too much cooling.

Compared to observations, GISS produces too little precipitation globally particularly over the western U.S., most of South America including the Amazon Basin, Russia, southeastern Asia and southern Africa. A study by Lin et al. [2006] found that GISS unrealistically produces more precipitation over the western Pacific than over the eastern Indian Ocean. GISS also fails to produce the observed precipitation minimum over the eastern Pacific trade wind cumulus region [Lin et al., 2006]. Dai [2006] found that the GISS model considerably underestimates tropical precipitation variability but has realistic cloud distribution relative to 17 other coupled models. The study by Dai also found that GISS overestimated the precipitation frequency and underestimates the intensity over the oceans. In addition, ENSO-related precipitation variability is too small in the GISS model.

2.3.3.1 20th Century

The IPCC AR4 Climate of the 20th Century experiment (20C3M) was used for the years 1901 to 2000. The initial state is taken from the preindustrial control (Plcntrl) experiment. Time-varying forcings include land use change, solar forcing, CO₂, CH₄, N₂O, CFC’s, tropospheric and stratospheric O₃, sulfates, dust, nitrates, organic and black carbon, sea salt and volcanic stratospheric aerosols. 2nd indirect aerosol effects were parameterized from interactive runs. The indirect impact of soot on ice albedo was also included [CMIP3 Climate Model Documentation, 2011; IPCC, 2007].
Figure 2.1 shows the 20th century zonal observed and modeled surface air temperature annual anomalies from the 1928-1978 average. GISS displays strong warming in the northern and southern high latitudes in the second half of the 20th century. Between 1901 and 1928, the high northern latitudes have stronger negative anomalies than seen in observations. By the end of the 20th century, the temperature anomalies are of a similar magnitude to the observations. However, the observations do not show minimum warming around 60N and 60S as seen in GISS.

Figure 2.2 is the globally averaged, land-only surface air temperature timeline from 1901 to 2100. The temperature is displayed as an anomaly from the 1971-2000 mean. In the 20th century, GISS displays global land temperatures with similar variability and magnitude as the observations.

Figure 2.3 shows the 20th century zonal modeled and observed precipitation annual anomalies from the 1928-1978 averages. GISS shows very little variability compared to the observations, which is expected from findings that GISS has unrealistic ENSO interdecadal variability and amplitude [Lin, 2007; AchutaRao and Sperber, 2006]. The variability in GISS is confined to a narrow band around the equator. In the observations the variability is more spread out through the tropics and subtropics. In the last decade of the 20th century, GISS displays the smallest precipitation anomalies of the century particularly in the tropics, subtropics and mid latitudes while this period does not represent a change in observations. The global mean land-only precipitation in Figure 2.2 shows GISS precipitation is greater than observations between 1901 and 1950. However, Figure 2.2 also highlights the lack of variability in GISS precipitation compared to observations.

The global mean land-only SDDI from 1901 to 2100 is displayed in Figure 2.4. The SDDI values were calculated using modeled and observed temperature and precipitation. Negative
SDDI indicates drier conditions. GISS has a larger mean SDDI than observations until around 1950, around the time GISS precipitation decreased to match observations. After 1950, GISS SDDI and observations become close.

Figure 2.4 also shows the global mean soil moisture timeline from 1901 to 2100 as anomalies from the 1971-2000 averages divided by the 1971-2000 standard deviation. GISS soil moisture appears to remain steady in the 20th century with small decreases around 1990 to 2000. In Chapter 1, it is hard to see any trend in the GISS global mean soil moisture in Figure 1.2 with average values of 475 kg/m² (although Figure 1.3 indicates a somewhat clearer decline). This is slightly below the 500 to 800 kg/m² range in the four LSMs between 1979 and 2009 discussed in Chapter 1 (Figure 1.1).

2.3.3.2 21st Century

The IPCC AR4 SRES A2 was used for the years 2001 to 2100. The initial state was taken from the 20C3M experiment. Time-varying forcing agents for SRES A2 include the same forcings as in the 20th century but at the levels prescribed by Nakicenovic et al. [2000]. Dust and sea salt aerosol forcings are set to constant or annually cyclic in the 21st century. 2nd indirect aerosol effects are included [IPCC, 2007].

Figure 2.5 is the zonal 20th century observed and 20th and 21st century modeled surface air temperature annual anomalies. GISS shows strong warming at all latitudes, particularly at high northern latitudes. Minimum temperature increases occur around 60S. Changes in the seasonal zonal mean surface air temperature are shown in Figure 2.6. In JJA, GISS temperatures rose at all latitudes with peaks at 30S, 20N and 40N. In DJF, temperatures also increased at all latitudes. The largest increase is in the high northern latitudes.

20th and 21st century precipitation anomalies are displayed in Figure 2.7. GISS has three
pronounced bands of precipitation increase: 15N to 15S, 40N to 90N (weakest increase) and 45S to 70S. Decreased precipitation is found in two bands: 15S to 45S and 15N to 40N. These zonal patterns strengthen over the course of the 21st century. The pattern also shows up in the JJA land-only zonal mean precipitation difference between the end of the 20th and 21st centuries (Figure 2.6). In DJF, most of the change in zonal land precipitation is in the southern hemisphere.

GISS soil moisture by the end of the 21st century appears to be decreasing in the 21st century (Figure 2.4). In Chapter 1, Figure 1.2 shows that GISS has global mean soil moisture that declines slowly between 1901 and 2100 with average values around 460 kg/m², which remains below the 1979-2009 average LSM soil moisture (Figure 1.1). Figure 2.9 shows the zonal soil moisture anomalies as they progress through the 20th and 21st centuries. Soil moisture decreases are widespread without much zonal coherence.

The SDDI trend over the 20th and 21st centuries is shown in Figure 2.4. GISS exhibits a steady decline over time. The JJA and DJF zonal change in SDDI for GISS show decreases (drying) all latitudes between 60S and 60N with increases at high northern latitudes (Figure 2.8). The evolution of zonal land-only SDDI changes can be more clearly seen in Figure 2.9. In Figure 2.9, GISS shows two drying bands: between 10N and 30N and 10S and 45S.

The 10N to 30N and the 10S to 45S bands partially correspond to downwelling in the JJA 1901 to 2100 zonal mean vertical velocity anomalies in Figure 2.10. Zonally, GISS displays an enhanced northern hemisphere JJA Hadley circulation in the southernmost region of the downwelling arm. Downwelling is also strengthened in the southern hemisphere poleward flank of the Hadley cell mainly during JJA but also in DJF.

GISS shows mild positive correlation between surface air temperature over land and SDDI in eastern North America (Figure 2.11). So with increased temperature, wetter conditions would be
expected. The opposite is true over the rest of the mid latitudes, tropics and subtropics where temperature and SDDI are strongly negatively correlated. Increased temperatures lead to increased evaporation and drier conditions. Precipitation and SDDI are positively correlated across the globe for GISS particularly around the Great Lakes in North America and the U.S. West coast.

The strongest negative correlations between soil moisture and surface air temperature in GISS occur over northern and southern Africa, southern Europe, and the southwestern U.S. (Figure 2.11). In these areas, as temperatures rise, soil moisture noticeably decreases. There are also regions that show increases in soil moisture when temperatures increase, such as over eastern North America, central Eurasia and a portion of northern South America. Soil moisture is positively correlated with precipitation globally but particularly in eastern North America, northern South America, eastern Europe and southern Africa for GISS.

2.3.4 Hadley Centre for Climate Prediction Coupled Model

The Hadley Centre for Climate Prediction Third Coupled Model (HadCM3) has a 1.25°×1.25° rigid lid ocean component with 20 layers [Gordon et al., 2000] and a 2.5°×3.75° atmosphere component with 19 layers [Pope et al., 2000]. The equilibrium climate sensitivity of HadCM3 is 3.3°C and it has a transient climate response of 2.0°C.

The Hadley Centre Third Atmosphere Model (HadAM3) [Pope et al., 2000] is the atmosphere component of the coupled model. HadAM3 has a large high-pressure bias in SLP over the winter pole and it has a cold bias at the surface and throughout most of the troposphere, particularly at high latitudes. The cold bias is the worst during the winter in the Northern Hemisphere. Regionally, surface temperatures have a tendency to be too cold in northern Eurasia and too warm in eastern North America. Pope et al. [2000] found that the seasonal variation is
exaggerated in HadAM3 in both hemispheres.

According to comparisons of the HadCM3 with observations, in the Southern Hemisphere, the tropical east Pacific and the Atlantic have too much heat going into the ocean surface, specifically on the Equator in the east Pacific [Gordon et al., 2000]. In the equatorial Pacific, there is too much cold-water upwelling consistent with overly strong low-level equatorial winds. There is also too much heat entering the ocean in the tropical and subtropical North Pacific and Indonesia/east Indian Ocean [Gordon et al., 2000].

Pardaens et al. [2003] found the HadCM3 hydrological cycle to be stronger than observations with too much global precipitation and evaporation. More specifically, the precipitation tends to be overestimated at mid to high latitudes particularly in the Southern Hemisphere and evaporation is overestimated at tropical to subtropical latitudes. The overestimation of evaporation is the likely cause of the shift to more saline conditions in the Atlantic Ocean. The meridional overturning circulation in the Atlantic Ocean is slightly too weak in HadCM3 when compared to observations [Gordon et al., 2000].

2.3.4.1 20th Century

The IPCC AR4 Climate of the 20th Century experiment (20C3M) was used for the years 1901 to 2000. The initial state is taken from the preindustrial control (PIcntrl) experiment. Forcings include CO₂, CH₄, N₂O, CFC’s, sulfate aerosol, volcanic aerosols, solar forcing, and sulfur chemistry without DMS and SO₂ background emissions. 1st aerosol indirect effects are included. There is also varying tropospheric and stratospheric O₃ [CMIP3 Climate Model Documentation, 2011; IPCC, 2007].

Figure 2.1 shows the 20th century zonal observed and modeled surface air temperature annual anomalies from the 1928-1978 average. HadCM3 displays strong warming at all latitudes in the
last twenty years of the 20th century. There are cold anomalies around 1930 and 1950 in the high northern latitudes in HadCM3 that occur at a time of warm anomalies in the observations. Generally, between 1901 and 1980 there is a lot of variability near the North Pole that isn’t seen in the observations. By the end of the 20th century, the temperature anomalies are more strongly positive than the observations. However, the observations do not show minimum warming around 45N and 45S as seen in HadCM3.

Figure 2.2 is the globally averaged, land-only surface air temperature timeline from 1901 to 2100. The temperature is displayed as an anomaly from the 1971-2000 mean. In the mid 20th century, HadCM3 shows global land temperature anomalies ~0.3°C below observations until about 1961. The variability in HadCM3 global surface air temperature is similar to observations.

Figure 2.3 shows the 20th century zonal modeled and observed precipitation annual anomalies from the 1928-1978 averages. HadCM3 shows very strong variability in the tropics compared to the observations. HadCM3 was shown to have an oscillation shorter than the observed ENSO period and a realistic ENSO amplitude, which helps explain the strong tropical variability in precipitation [Lin, 2007; AchutaRao and Sperber, 2006]. In the observations the variability is more spread out through the tropics and subtropics. HadCM3 precipitation anomalies display a noticeable positive trend in the latter portion of the 20th century in the northern and southern hemispheres centered on 60N and 60S that is slightly larger than the northern mid latitude increase in observations. The global mean land-only precipitation in Figure 2.2 shows HadCM3 slightly wetter than observations until around 1950.

The global mean land-only SDDI from 1901 to 2100 is displayed in Figure 2.4. The SDDI values were calculated using modeled and observed temperature and precipitation. Negative SDDI indicates drier conditions. HadCM3 has a larger mean SDDI than observations during the
mid 20th century, around the time when temperatures in HadCM3 were lower than observations. Around 1970, HadCM3 becomes drier than observation-based SDDI.

Figure 2.4 also shows the global mean soil moisture timeline from 1901 to 2100 as anomalies from the 1971-2000 averages divided by the 1971-2000 standard deviation. HadCM3 soil moisture shows small decreases in the last few years of the 20th century. In Chapter 1, Figure 1.2 shows that HadCM3 has global mean soil moisture that shows no strong trend by the year 2000 with average steady values around 800 kg/m². This is in the same range as the soil moisture in the four LSMs discussed in Chapter 1 (Figure 1.1).

2.3.4.2 21st Century

The IPCC AR4 SRES A2 was used for the years 2001 to 2100. Time-varying forcing agents for SRES A2 include CO₂, CH₄, N₂O, CFC’s, HFC’s, stratospheric and tropospheric O₃, and sulfur emissions according to SRES A2 scenario guidelines [CMIP3 Climate Model Documentation, 2011; IPCC, 2007; Johns et al., 2003]. 1st indirect aerosol effects are included. Volcanic aerosols and solar forcings are set to constant or annually cyclic for the 21st century.

Figure 2.5 is the zonal 20th century observed and 20th and 21st century modeled surface air temperature annual anomalies. HadCM3 shows strong warming at all latitudes, particularly at high northern and southern latitudes. Minimum temperature increases occur around 60S. Changes in the seasonal zonal mean surface air temperature are shown in Figure 2.6. In JJA, HadCM3 temperatures rose at all latitudes with peaks at 10S and 45N. In DJF, temperatures also increased at all latitudes. The largest increase is in the high northern latitudes.

20th and 21st century precipitation anomalies are displayed in Figure 2.7. HadCM3 has increased precipitation from 45N to 90N and from 45S to 70S. There are weak precipitation decreases centered on 30N and 30S. In Figure 2.7, there is also a band of increased precipitation
and decreased precipitation at the equator related to a northern shift in the ITCZ due to warming over northern landmasses. These patterns tend to strengthen over the course of the 21st century. The pattern also shows up in the JJA land-only zonal mean precipitation difference between the end of the 20th and 21st centuries (Figure 2.6). In DJF, most of the change in zonal land precipitation is in the southern hemisphere.

HadCM3 soil moisture by the end of the 21st century appears to be decreasing strongly in the 21st century (Figure 2.4). In Chapter 1, Figure 1.2 shows that HadCM3 has global mean soil moisture that declines steadily in the 21st century with average values around 790 kg/m², which remains below the 1979-2009 average LSM soil moisture (Figure 1.1). Figure 2.9 shows the zonal soil moisture anomalies as they progress through the 20th and 21st centuries. Soil moisture changes in HadCM3 are zonally unfocused with the exception of a strong decrease between 40N and 70N, which are the only latitudes showing increasing fluvial conditions in SDDI. There is only a small increase in upwelling in the northern hemisphere over those latitudes (Figure 2.10).

The SDDI trend over the 20th and 21st centuries is shown in Figure 2.4. HadCM3 exhibits a steady decline over time. The JJA and DJF zonal change in SDDI for HadCM3 show decreases (drying) all latitudes between 60S and 80N with increases at high northern latitudes (Figure 2.8). The evolution of zonal land-only SDDI changes can be more clearly seen in Figure 2.9. In Figure 2.9, HadCM3 shows clear drying bands cover all latitudes between 50N and 55S.

SDDI drying in the southern hemisphere partially corresponds with downwelling in the JJA and DJF 1901 to 2100 zonal mean vertical velocity anomalies in Figure 2.10. Zonally, HadCM3 displays a northward shift in the ITCZ in both JJA and DJF, which can also be seen in precipitation anomalies in Figure 2.7 and most likely associated with warming over northern hemisphere land masses. There is also some enhanced downwelling in both hemispheres around
40S and 40N in JJA and DJF.

HadCM3 shows mild positive correlation between surface air temperature over land and SDDI in eastern Asia, Siberia and Alaska (Figure 2.11). With increased temperature, wetter conditions would be expected. The opposite is true over the rest of the mid latitudes, tropics and subtropics where temperature and SDDI are strongly negatively correlated with the exception of the eastern U.S., which has only a mildly negative correlation. Increased temperatures lead to increased evaporation and drier conditions. Precipitation and SDDI are positively correlated across the globe for HadCM3 particularly northeastern South America and the west coast from Siberia to China.

The strongest negative correlations between soil moisture and surface air temperature in HadCM3 occur over the northern coast of South America, southern Europe, northern Canada and central Russia (Figure 2.11). In these areas, as temperatures rise, soil moisture noticeably decreases. There are also regions that show increases in soil moisture when temperatures increase, such as over central Africa and central Eurasia. Soil moisture is positively correlated with precipitation globally except central Russia and northern Canada.

2.3.5 Center for Climate Systems Research at the University of Tokyo/National Institute for Environmental Studies/Frontier Research Center for Global Change Coupled Model

The Model for Interdisciplinary Research on Climate (MIROC) Model V3.2 is a collaboration between the Center for Climate Systems Research at the University of Tokyo, the National Institute for Environmental Studies and the Frontier Research Center for Global Change. They have high and medium resolution models. We are using data from the medium resolution coupled model, which has a ~2.8°×2.8° atmosphere component with 20 layers [K-I Developers,
2004] and a free surface ocean component with 0.5°-1.4°×1.4° resolution and 43 layers [K-1 Developers, 2004]. The land component is based on Oki and Sud [1998]. MIROC V3.2 with medium resolution has an equilibrium climate sensitivity of 4.0°C and a transient climate response of 2.1°C, which makes it the warmest of all models in this study. In this model, no indirect aerosol effects are accounted for; only the direct effects of sulfate aerosols are included.

Like HadCM3 and GFDL, MIROC has a tropospheric cold bias. It is seen particularly around the tropopause and is attributed to insufficient absorption of shortwave radiation by ozone. Some other limitations of the model are that the TOA radiation budget has a downward imbalance of 1 W/m², the sea ice is smaller than observations in the Southern Hemisphere, there is too much high cloud cover and the amplitude of ENSO is smaller than observations [CMIP3 Climate Model Documentation, 2011]. As seen in Chapter 1, MIROC has relatively high soil moisture values due to many factors including the depth (4m) of the land surface. In addition, the MIROC model was spun-up with a saturated surface and the frozen subsurface water in the high latitudes moves very slowly potentially overestimating soil moisture [personal communication with T. Oki].

2.3.5.1 20th Century

The IPCC AR4 Climate of the 20th Century experiment (20C3M) for MIROC begins in the mid 19th century and ends in the year 2000. The initial state is taken from the preindustrial control (PIcntrl) experiment. Forcings include CO₂, CH₄, N₂O, CFC’s, stratospheric and tropospheric O₃, sulfate aerosols, black and organic carbon, dust, volcanoes, sea salt, land use and solar forcing. 1st and 2nd indirect aerosol effects are included in this simulation. There was a problem with the volcanic aerosol distribution in this experiment. The vertical distribution was intended to have a maximum value just above the tropopause. However, the maximum always occurs at
50hPa regardless of the temperature profile in this experiment [CMIP3 Climate Model Documentation, 2011; IPCC, 2007].

Figure 2.1 shows the 20th century zonal observed and modeled surface air temperature annual anomalies from the 1928-1978 average. MIROC displays strong warming at high northern latitudes in the last fifteen years of the 20th century. Otherwise MIROC does show temperature anomalies very similar to observations. The warm anomalies that occur in the observations in the 1940s and 1950s in the high northern latitudes do not appear in the MIROC simulation. By the end of the 20th century, the temperature anomalies are more strongly positive than the observations only near the North Pole. Figure 2.2 is the globally averaged, land-only surface air temperature timeline from 1901 to 2100. The temperature is displayed as an anomaly from the 1971-2000 mean. In the 20th century, MIROC shows global land temperatures close observations in magnitude and variability.

Figure 2.3 shows the 20th century zonal modeled and observed precipitation annual anomalies from the 1928-1978 averages. The variability in MIROC is confined to a narrow band around the equator. In the observations the variability is more spread out through the tropics and subtropics. MIROC was found to have an unrealistically long ENSO oscillation that helps explain this behavior in precipitation. The global mean land-only precipitation in Figure 2.2 shows that MIROC precipitation is greater than observations from 1901 to 1960. Figure 2.2 also highlights that MIROC has similar global variability in precipitation over land.

The global mean land-only SDDI from 1901 to 2100 is displayed in Figure 2.4. The SDDI values were calculated using modeled and observed temperature and precipitation. Negative SDDI indicates drier conditions. MIROC has a larger mean SDDI than observations until around 1960, around the time MIROC precipitation decreased to match observations. After 1960,
CCCma SDDI and observed SDDI become close.

Figure 2.4 also shows the global mean soil moisture timeline from 1901 to 2100 as anomalies from the 1971-2000 averages divided by the 1971-2000 standard deviation. MIROC soil moisture is extremely variable throughout the 20th century. By the year 2000, it appears to be decreasing slightly. In Chapter 1, Figure 1.2 shows that MIROC has global mean soil moisture with average values of 1250 kg/m² in the 20th century. This is much higher than the soil moisture in the four LSMs discussed in Chapter 1, which ranged from 500 to 800 kg/m² between 1979 and 2009 (Figure 1.1).

### 2.3.5.2 21st Century

The IPCC AR4 SRES A2 storyline is used for the 21st century. There is overlap between these two experiments; the simulation begins in the state of the year 1990 from the 20C3M experiment. We used 1901-2000 from the 20C3M experiment and 2001-2100 from the SRES A2 experiment. Forcing agents for SRES A2 include CO₂, CH₄, N₂O, CFC’s, tropospheric and stratospheric O₃, sulfate aerosols, black and organic carbon, dust and sea salt [CMIP3 Climate Model Documentation, 2011; IPCC, 2007]. 1st and 2nd indirect aerosol effects are included in the 21st century. Volcanic aerosols, land use and solar forcings are set to constant values or are annually cyclic in this simulation.

Figure 2.5 is the zonal 20th century observed and 20th and 21st century modeled surface air temperature annual anomalies. MIROC shows strong warming at all latitudes, particularly at high northern latitudes. Minimum temperature increases occur around 60S. Changes in the seasonal zonal mean surface air temperature are shown in Figure 2.6. In JJA, MIROC temperatures rose at all latitudes with a peak from 40N to 60N. In DJF, temperatures also increased at all latitudes. The largest increase is in the high northern latitudes.
20th and 21st century precipitation anomalies are displayed in Figure 2.7. MIROC has three pronounced bands of precipitation increase: 15N to 15S, 50N to 90N and 50S to 70S. Decreased precipitation is found in two bands: 15S to 50S and 15N to 50N. These zonal patterns strengthen over the course of the 21st century. The pattern also shows up in the JJA land-only zonal mean precipitation difference between the end of the 20th and 21st centuries (Figure 2.6). In DJF, most of the change in zonal land precipitation is in the southern hemisphere.

Figure 2.4 shows that MIROC soil moisture by the end of the 21st century appears to be decreasing slightly. In Chapter 1, Figure 1.2 shows that MIROC has steadily decreasing global mean soil moisture with average values around 1210 kg/m² by the year 2100, which is still much higher than the four LSMs discussed in Chapter 1 (Figure 1.1). Figure 2.9 shows the zonal soil moisture anomalies as they progress through the 20th and 21st centuries. Soil moisture decreases are focuses in three bands: 15N to 55N, 0 to 25S and 35S to 45S. There is also a wetter trend between 50N and 60N, 0 to 15N and 25S to 35S. These changes in soil moisture can be partially explained by shifts in mean vertical velocity in the 21st century (Figure 2.10).

The SDDI trend over the 20th and 21st centuries is shown in Figure 2.4. MIROC exhibits a steady decline over time. The JJA and DJF zonal change in SDDI for MIROC show decreases (drying) all latitudes between 60S and 80N with increases at high northern latitudes (Figure 2.8). The evolution of zonal land-only SDDI changes can be more clearly seen in Figure 2.9. In Figure 2.9, MIROC shows two pronounced drying bands: between 20N and 45N and 10S and 55S.

Changes in zonal mean vertical velocity anomalies for MIROC show a southward shift in the ITCZ in JJA and a northward shift in DJF, which can also be seen in the precipitation anomalies (Figures 2.7 and 2.10). MIROC also displays a poleward shift in Hadley cell downwelling and Ferrell cell upwelling in the southern hemisphere in JJA and DJF. In addition there is enhanced
downwelling around 40N in DJF. It is evidence in MIROC that there are coherent shifts in mean vertical circulation in the 21st century.

MIROC shows mild positive correlation between surface air temperature over land and SDDI in eastern Siberia, the Tibetan Plateau and Alaska (Figure 2.11). As temperatures increase, wetter conditions would be expected. The opposite is true over the rest of the mid latitudes, tropics and subtropics where temperature and SDDI are strongly negatively correlated. Increased temperatures lead to increased evaporation and drier conditions. Precipitation and SDDI are positively correlated across the globe for MIROC particularly around the southern and central U.S., eastern Siberia, Alaska and the eastern tip of South America.

The strongest negative correlations between soil moisture and surface air temperature in MIROC occur over southern Africa, southern Europe, the U.S. and most of South America (Figure 2.11). In these areas, as temperatures rise, soil moisture noticeably decreases. There are also regions that show increases in soil moisture when temperatures increase, such as over northern Canada and central Eurasia. Soil moisture is positively correlated with precipitation globally but particularly in eastern South America for MIROC.

2.4 Model Intercomparison

In the previous section, each models was examined independently. In this section, we look at the range in climate responses from all of the models, one variable at a time. As for an overall comparison, a study by Reichler and Kim [2008] looked at how well coupled models simulate today’s climate and found that GFDL performed best followed by HadCM3, CCCma, MIROC and finally GISS. Although it should be noted that CCCma received an unfair advantage by using flux adjustments.
2.4.1 Surface Air Temperature

A strong global warming signal is seen globally and zonally in all five models by the end of the 21st century (Figures 2.2 and 2.5). The range in global mean surface air temperature by the 2100 is 4°C to 6°C above the 1971-2000 average (excluding Antarctica and Greenland). All of the models stay close in their projections until around 2050 where two of the warmer models (HadCM3 and MIROC) branch off from the models that predict more moderate warming (GFDL and CCCma). GISS projections are at the low end of the warming; it has the lowest equilibrium climate sensitivity of all the models in this study. Observations of 20th century observed global mean temperature anomalies agree well with GCM temperature anomalies with the exception of CCCma. The temperature anomalies are with respect to the 1971-2000 mean, which was higher for CCCma than any other model (Figure 2.12). Early 20th century temperatures in CCCma were not lower than other models, there was just more of a temperature change from 1901 to 2000 than in the other models.

Figure 2.12 displays maps of JJA and DJF mean surface air temperature for the years 1971 to 2000 and the difference between the 2071-2100 mean and the 1971-2000 mean for all five GCMs. During the last 30 years of the 20th century in JJA, there are some similarities between models. Northern Africa and the Middle East have high temperatures and temperatures are low over Antarctica. All of the models are able to get these basic temperature features. However, there are many large differences in this 30-year mean field. For example, models do not agree on temperatures over the western Pacific, the United States and this Indian Ocean. Figure 2.13 shows the 1971-2000 mean observations of JJA and DJF surface air temperature. There are a number of regional similarities and differences between the observations and models. The models tend to overestimate temperatures particularly in the high latitudes, tropics and
subtropics. Obviously, differences in the latitudinal temperature gradients among the models will influence atmospheric dynamics and in turn regional projections, which will be discussed in detail in Chapter 4.

The bottom two rows of Figure 2.12 show the JJA and DJF surface air temperature anomalies for all five models for the period 2071 to 2100. In JJA, temperature increases relative to the 20th century can be seen focused mainly over the continents in all models. In DJF, temperature increases are also focused over land but mainly over the Arctic due to increased absorption of radiation due to decreased albedo.

2.4.2 Precipitation and Cloud Cover

Over land, some models show steady increases in precipitation over the 21st century and others exhibit only minor increases (Figure 2.2). Globally, the 5 models show increased precipitation ranging from 1.5 to 6 mm/day by the year 2100 over land. In theory, warmer temperatures in the troposphere lead to an enhanced cooling rate, which in turn causes an increase in precipitation. However, IPCC concludes that, “global mean precipitation should respond more to changes in shortwave forcing than CO₂ forcing,” (IPCC 2007) since the efficiency of radiative cooling is decreased by the increase in atmospheric CO₂. The decreased efficiency of radiative cooling (although still associated with an increase in total radiative cooling) thus requires less of an increase in latent heating in the atmosphere (i.e., from moisture condensation) for balance. If we consider cloud cover as a proxy for the amount of shortwave radiation reaching the surface, then a decrease in cloud cover should result in increased precipitation. Accordingly, models experiencing the largest decreases in global cloud cover should also have the largest increase in precipitation. However, it seems that models with the largest decreases in cloud cover globally actually exhibit the smallest increase in precipitation both globally and over land only (Figure
2.2). It is unclear whether global mean precipitation responds more to changes in shortwave forcing than CO₂ forcing but shortwave forcing is not dominant.

The GCM seasonal precipitation for 1971-2000 and the difference between the 2071-2100 mean and the 1971-2000 mean is shown in Figure 2.14. Comparing the 1971-2000 images to the observations in Figure 2.13, it becomes obvious that although many of the same features are present in the models and observations, such as strong precipitation over Southeast Asia in JJA, they are almost always shifted or contorted in a way that would impact regional climates. Figure 2.7 shows that a strong zonal pattern is emerging in all of the models in the 21st century: decreased precipitation around 10N-40N and 10S-40S and increased precipitation at the equator and mid to high latitudes. More specifically over land, the precipitation decreases are focused around 40N and 10N-15N in JJA and 40S and 10S-15S in DJF (Figure 2.6).

The bottom two rows of Figure 2.14 show the JJA and DJF 2071-2100 mean precipitation anomalies. It is clear from the maps in Figure 2.14 that the zonal picture is over-simplifying future regional precipitation changes. There are innumerable differences between the models in terms of precipitation that, as mentioned above, often involve similar patterns contorted from one model to the next. For example, precipitation over Australia, the tropical Pacific and China are particularly variable. Similar to precipitation, a comparison of the zonal average vertical velocity (Figure 2.10) and the vertical velocity global maps (Figure 2.15) reveal an oversimplification of regional changes in Hadley circulation in the 21st century in the zonal average discussion. Regional changes in vertical velocity will be discussed further in Chapter 4.

A study by Dai [2006] compared 20th century precipitation characteristics in 18 coupled climate models (including the 5 models in this study) to global monthly precipitation from CMAP and GPCP v2, GPCP pentad precipitation and 3-hourly data from TRMM and surface
observations. *Dai* [2006] found that CCCma, MIROC and HadCM3 produce the most realistic patterns of tropical precipitation. GFDL was found to overestimate the standard deviation in annual precipitation in the equatorial central and western Pacific, while GISS underestimates the standard deviation in annual tropical precipitation. Over low latitudes, GFDL and HadCM3 were noted for producing over 95% (too much) of their total precipitation as convective precipitation and producing too little stratiform precipitation. MIROC, CCCma and GISS were found to produce relatively realistic stratiform precipitation fields. *Dai* [2006] found that MIROC does well in reproducing daily patterns of precipitation frequency and intensity, while GISS overestimates the frequency and underestimates the intensity. In general the models tend to underestimate heavy precipitation events and overestimate light precipitation. MIROC was also found to produce relatively realistic diurnal precipitation but the warm-season convection begins too early and happens too frequently at reduced intensity.

### 2.4.3 Snow

Figure 2.16 shows the observed and modeled monthly anomalies of mean snow cover extent over land in the Northern Hemisphere between November 1966 and January 2011. Observations were obtained from the Global Snow Lab at Rutgers University. The GCM projections for snow cover were only available from CCCma, GISS and MIROC out of the five models in this study and areal extents were calculated using globally weighted sums. The anomalies are with respect to the November 1966 to January 2011 means, which equaled 26.49, 23.65 and 20.58 million km$^2$ for CCCma, GISS and MIROC respectively. CCCma and GISS do the best job of matching the observed average of 25.11 million km$^2$ in the Northern Hemisphere during that period. However, the modeled month-to-month variability of snow cover extent does not compare favorably with the observations. Observation between 1966 and 1992 show snow cover extent
fluctuating by roughly twice the amount that the models project. Also, individual events such as
the high snow extent in the late 1970s and the lows in the late 1980s are not reproduced in the
models.

The GCMs show a slight downward trend in snow cover extent during this period that is also
present in the observations. Figure 2.16c shows the 1901 to 2100 projections of monthly mean
anomalies of snow cover extent in the three GCMs along with the 1966 to 2011 observations.
The models continue to display a negative trend in the 21st century, which ends with snow cover
extent reduced by 3 to 6 million km². MIROC, which already had the lowest 1966 to 2011 mean
snow cover extent, shows the most severe decrease in the 21st century.

Figure 2.17 displays the snow amount (kg/m²) for all five models during December, January
and February for 1971 to 2000 and 2071 to 2100. The snow cover extent in GFDL and HadCM3
(these two models were missing snow cover data) looks roughly similar to the other three
models. All models except HadCM3 and GISS project a decrease in snow amount by the late 21st
century. All models agree that snow amount will increase in northern Siberia and northern
Canada and decrease from southern Alaska down to the Rockies and across Scandinavia and
eastern Europe. In HadCM3, increases in snow amount occur in central Greenland, northern
Alaska and Antarctica as well. In the GISS model, the DJF snow increases also are focused on
the Himalayan Plateau and the coastline of Greenland.

The GISS and CCCMA models were able to most closely match observed snow cover extent.
They do agree on regions for snow amount increases and decreases along with the other models
but the disagree on the global sign of the snow amount change. However, it appears that GISS is
overestimating snow amount over the Tibetan Plateau with respect to the other models, which
leaves room for doubt in its global snow amount projections.
2.4.4 SDDI and Soil Moisture

Over the next 100 years, global-average SDDI predictions over land steadily decrease, indicating severe drying globally by the year 2100 (Figure 2.4). In contrast, global-average soil moisture projections show almost no change in the 21st century in all models except the HadCM3 model, which shows a steady decrease (Figure 2.4). IPCC [2007] found that droughts have become more common, especially in the tropics and subtropics, since the 1970s, which is in agreement with modeled and observed SDDI. However, both SDDI and soil moisture do agree that in all models the percentage of gridboxes experiencing both extreme drought and extreme fluvial conditions at the 5% level continues to increase over the next century (Figures 2.18 and 2.19). Because raw SDDI and soil moisture values give little intuitive understanding of the severity of drought, Figures 2.18 and 2.19 display the severity of water availability relative to prior conditions, as a percentage of time during which those conditions occurred in the past. Five percent drought indicates a drought of a severity seen during only 5% of the control time period (1928-1978). Figure 2.18 shows an increase in both dry and wet extreme conditions for soil moisture, which results in very little change in the global-average shown in Figure 2.4. HadCM3 shows the globally averaged decrease in soil moisture in Figure 2.4 because the extremely wet conditions do not occur as much as the extremely dry conditions (Figure 2.18). In the SDDI analysis in Figure 2.19, extreme drought outweighs extreme fluvial conditions although both show increases, which explains why global-average SDDI shows an overall drying trend. For the 5% drought, the soil moisture percentage increases are in general smaller than those for SDDI, especially in summer, while the 5% flood condition increases are greater than for the SDDI in both seasons.

The impact of the IPCC SRES A2 storyline choice for the 21st century is in most cases
smaller than the differences between the GCMs. Figure 2.20 shows the 1901 to 2100 timeline for SDDI projections for all five GCMs for both the A2 and A1B scenarios. The A1B scenario gives more severe projections for SDDI over the 21st century. It is likely that all SRES storylines would have a global drying trend in SDDI due to increased temperatures.

The zonal changes in the SDDI and soil moisture (% change) from the end of the 20th to 21st centuries are shown in Figure 2.8. Table 2.3 lists the Palmer Drought Severity Index classifications, which can reasonably be applied to SDDI because of their similar formulations (Chapter 1) and high correlation in the U.S. [Rind et al., 1990]. In both summer and winter, changes from the 20th to 21st century show that that SDDI experiences decreases (drier conditions) in the tropics ranging from mild (GISS and GFDL) to extreme (HadCM3). There is more agreement among the models that there are extreme decreases in the mid latitudes. In the Arctic, the models show increased SDDI (wetter conditions) ranging from moderate to extreme.

Soil moisture percentage changes between the end of the 20th and 21st centuries show the equator getting slightly wetter over land consistent with increased upwelling (Figure 2.8). There is drying around 35N-40N and 35S-40S and in some models around 10N-30N and 10S-30S. The lower latitude tropical portions of this region (10N-15N and 10S-15S) are due to changes in the mean circulation and precipitation over land. The subtropical changes seem to be more associated with warming temperatures and increased evaporation. The strong variability in GFDL is due to the total global soil moisture being an order of magnitude less than in the other models. Generally, each model looks similar in both seasons, which implies that the lifetimes of both SDDI and soil moisture are long enough that they impose a consistent response throughout the year.

Figure 2.21 displays maps of JJA Land Surface Model (LSM) soil moisture for the years 1979
to 2010. The corresponding JJA GCM soil moisture over the same period is in the top row of Figure 2.22. In addition, Figure 2.22 shows the DJF 1979-2010 mean soil moisture and JJA and DJF seasonal anomalies for future projections (2071-2100). The disagreements on soil moisture among the GCMs and LSMs are primarily due to differences in soil moisture depths, which lead to very different soil moisture magnitudes. Although the magnitudes of soil moisture in the various models disagree, there are some common patterns that emerge, such as GFDL, HadCM3 and MIROC all showing patterns of high soil moisture at high northern latitudes similar to the LSMs in Figure 2.21. Also all of the GCMs and LSMs have relatively high soil moisture over notoriously wet regions such as the Amazon Basin and low soil moisture over the world’s deserts. However, a brief examination of Figures 2.21 and 2.22 shows that the differences in soil moisture between models tend to outweigh the similarities.

JJA and DJF soil moisture means in Figure 2.22 show very little difference, indicating that soil moisture does not show large seasonal shifts in the GCMs. Moving into the 21st century, soil moisture patterns show very different regional changes in each GCM, which will be discussed in detail for the regions of interest in Chapter 4. However, there are no obvious large global or zonal patterns.

Figure 2.23 shows the maps of JJA and DJF mean SDDI for 1971 to 2000 calculated using CRU TS 2.0, 0.5-degree global temperature and precipitation datasets [Mitchell and Jones, 2005]. Figure 2.24 gives the corresponding seasonal SDDI for 1971 to 2000 (top two rows) as well as 2071 to 2100 (bottom two rows), calculated using temperature and precipitation input from GCMs. Observed 1971-2000 JJA SDDI most closely resembles GFDL at high northern latitudes. The other GCMs have SDDI values that are too high (too wet). In JJA, over North and South America and Australia, none of the GCMs are able to reproduce the pattern of wet
conditions. Africa matches fairly well between observed SDDI and the models. In DJF, CCCma does the best job in matching the SDDI patterns over North America and Europe but has entirely too much drying over Australia. MIROC does the best job over Australia.

JJA and DJF SDDI means in Figure 2.24 show a clear difference, indicating that SDDI has larger seasonal shifts than soil moisture in the GCMs. Moving in to the 21st century, SDDI patterns look dramatically more dry than the 20th century for all five GCMs. According to Table 2.3, most land surface in the last 30 years of the 21st century is in at least moderate drought conditions.

Figures 2.21-2.24 give a good indication of the long-term mean state of soil moisture and SDDI in the 20th and 21st centuries. In addition disagreements between models for both SDDI and soil moisture, there is also very little agreement between the two water availability measures.

2.4.5 GCM Comparisons using Interpolated Grids

There is often a wide range in GCM projections for any given variable as is illustrated in many of the figures in this chapter. To understand large-scale agreement among surface air temperature, precipitation, soil moisture and SDDI and how it changes over time, we looked at the sign of the change between the 1901-1920 mean conditions and the 1981-2000 mean conditions as well as the difference between the 1981-2000 and 2081-2100 mean conditions. Table 2.4 shows the percentage agreement between the five GCMs we considered, expressed as the percentage of land grid boxes for which all five models agreed on the direction of change of the four climate variables. We conducted this gridbox-to-gridbox comparison by interpolating the grids of four of the models to the size of the model with the coarsest resolution, a 4° by 5° grid.

The agreement between models for the change between the early and late 20th century is
generally lower than the agreement between the late 20th century and late 21st century. Almost 83% of land gridboxes have the same direction of temperature change between the early and late 20th century. This agreement climbs to 100% for the 20th to 21st century difference. The same trend occurs for precipitation (16.26% to 47.83%), soil moisture (9.76% to 13.96%) and SDDI (38.89% to 56.91%). The least agreement between models for a single variable is on the sign of soil moisture changes as would be expected from Chapter 1. The only scenario that shows a decrease in model agreement in the 21st century is when the sign of temperature and soil moisture changes agree. Only about 3% of gridboxes showed agreement in this relationship in the 20th century. This dropped to approximately 2% in the 21st century. As temperatures rise, models agree that increasing soil moisture is becoming more rare.

The strongest agreement between variables is the inverse relationship between temperature and SDDI. Negative SDDI changes (drier conditions) are associated with increasing temperatures, suggesting temperature change is its dominant factor via influence on potential evaporation. Precipitation and temperature changes also have a fairly strong agreement among models (36.72%) in the 21st century. However changes in temperature and precipitation compete against one another in their influence on water availability measures, helping to explain the minimal agreement on the sign of soil moisture changes. In the 21st century, there is unanimity on the sign of the precipitation and soil moisture changes in only 7.45% of the gridboxes, and complete agreement on the inverse relationship between temperature and soil moisture in only 12.2%.

The influence of climate change can be seen clearly in the almost every relationship in Table 2.4. Both the relationships between temperature and SDDI as well as temperature and precipitation show significant increases in model agreement between the 20th and 21st centuries.
It should also be noted that although the agreement between soil moisture and SDDI changes is low, it does increase by over 100% in the 21st century. However, considering just these five models, in only 1 out of every 8 gridboxes is there a unanimous indication of the sign of future water availability change.

As a final check on the validity of the 20th century relationships, the same analysis was performed with observed 1901-1920 and 1981-2000 surface air temperature, precipitation and SDDI. The third column of Table 2.4 shows the percentage of gridboxes in which the multi-model GCM mean agrees with the sign of change in the observations. Note: percentages are larger due to the fact that only 2 items are being compared instead of 5 in the first two columns. The same general relationships exist with the observations; temperature increases are found in many of the same grid boxes as decreased SDDI and precipitation and SDDI agree on the sign of change in many more gridboxes than they disagree.

2.5 Conclusions

This chapter has explored the characteristics, biases and 20th and 21st century water availability projections of five GCMs: CCCma CGCM3.1 T47, GFDL CM2.1, GISS ER, HadCM3 and MIROC V3.2 (medium resolution). This subset of five IPCC AR4 GCMs is representative of the larger group in terms of spatial resolution, climate sensitivity, atmospheric forcing and ENSO interdecadal variability and magnitude.

CCCma is the only model in this study with flux corrections. 20th century projections indicate surface air temperatures are overestimated in the final few decades particularly at high latitudes and CCCma has shown to be poor at modeling observed ENSO variability [Lin, 2007; AchutaRao and Sperber, 2006]. The model shows a strengthening pattern through the 21st century of decreased precipitation in the subtropics and increased precipitation at the poles and in
the tropics. Overall by the year 2100, soil moisture increases and SDDI shows a steady drying trend.

GFDL shows large variability in both surface air temperature and precipitation. It is the model with the most realistic ENSO in this study \cite{Lin2007, AchutaRao2006}. It is also the only land scheme in this study to use a bucket model as opposed to layers. The global mean soil moisture in GFDL is lower than all the other models by an order of magnitude. This model shows precipitation increasing steadily at mid and high latitudes with strengthening decreases centered on 30N and 30S. SDDI indicates global drying with decreases at all latitudes except high northern latitudes. Soil moisture shows smaller decreases.

GISS has the lowest equilibrium climate sensitivity and transient climate response of all the models in this study. The model shows very little precipitation variability in the tropics and has been shown to have an unrealistic ENSO \cite{Lin2007, AchutaRao2006}. There is a pattern of increasing precipitation in the tropics and high and mid latitudes and decreasing precipitation in the subtropics throughout the 21st century. SDDI shows steady drying everywhere with the exception of the high northern latitudes. Soil moisture decreases to a lesser degree throughout the 21st century.

HadCM3 has a realistic ENSO amplitude but the strong variability in precipitation in the tropics has been shown to have too short of an oscillation for a realistic ENSO \cite{Lin2007, AchutaRao2006}. Precipitation continues to increase in the high and mid latitudes and there is a weak decrease in precipitation centered on 30N and 30S throughout the 21st century. Precipitation increases in the southern tropics and increases in the northern tropics potentially due to a northward shift in the ITCZ due to increased warming over land in the northern hemisphere. SDDI decreases at all latitudes except over the high northern latitudes. Soil
moisture decreases more in the 21st century in HadCM3 than in any other model in this study because increased drought is not offset by as much extreme flooding.

MIROC has the highest equilibrium climate sensitivity of all the models in this study. It also did the best job matching the observed zonal temperature anomaly timeline in the 20th century. Precipitation shows very little variability in the tropics. Lin [2007] found that MIROC has an ENSO oscillation that is too long. Precipitation increases in the tropics and mid and high latitudes and decreases in the subtropics. SDDI shows continuous drying between 2000 and 2100 except in the high northern latitudes. Of all five models, MIROC has the largest store of global soil moisture, which steadily decreases throughout the 21st century.

When the models are compared to one another in terms of surface temperature, precipitation, snow, SDDI, and soil moisture, a number of similarities and differences emerge. All of the models tend to overestimate temperatures in the high latitudes, tropics and subtropics. They also are in agreement that 21st century temperature increases in JJA are focused over the continents and DJF increases are also over land but mainly over the Arctic. All 5 models show increased precipitation over land and precipitation decreases focused around 40N and 10N-15N in JJA and 40S and 10S-15S in DJF. Many show the same regional dynamic shifts in precipitation. However they are shifted and contorted in ways that impact each model differently. Snow cover extent variability with time is poorly represented in CCCma, GISS and MIROC but they all showed similar trends of decreasing snow cover extent with observations in the 21st century. Although there are many disagreements between the two water availability measures, soil moisture and SDDI agree that in all models the percentage of gridboxes experiencing both extreme drought and extreme fluvial conditions at the 5% level continues to increase over the next century.

In Chapter 1, the emphasis was about understanding the differences between two water
availability measures, SDDI and soil moisture. In this chapter, the focus is on exploring the
different responses of the models. Both chapters have highlighted large differences between both
the measure and the models. While there is sometimes a wide range in values for variables from
different models, the range is small compared to the difference between SDDI and soil moisture
(Figure 1.7). Chapter 3 will explore a variety of ways in which the gap between the two water
availability measures can be bridged.
3 Bridging the gap between SDDI and Soil Moisture

3.1 Introduction

Chapter 1 explores viable methods of measuring global water availability and Chapter 2 analyzes the model characteristics and the range of projections over the next century. This chapter isolates the elements of the water availability measures that contribute to their differences. Soil moisture has consistently shown milder global decreases in future water availability than SDDI. This chapter will explore the three major differences between SDDI and soil moisture calculations that may shed some light on why their future projections diverge:

1) How evaporation is approximated for each measure,
2) Their dependence on previous months’ conditions and
3) The inclusion of additional variables other than evaporation and precipitation.

3.1.1 Evaporation approximations

In the SDDI formulation, the evaporation represents the atmospheric demand for moisture and is therefore set to a maximum value, the potential evapotranspiration, which is the evaporation expected over a completely wet surface. SDDI uses the Thornthwaite method to calculate the potential evapotranspiration, a method that has been shown to be much smaller than any other discussed in Chapter 1.

Evaporation in GCMs, the source for modeled soil moisture in this study, is determined by multiplying the aerodynamic potential evapotranspiration by a scaling factor that will be referred to as $\beta$. $\beta$ ranges from zero in very dry conditions to one in well-watered conditions. The aerodynamic method for calculating potential evapotranspiration produces much larger values
than the Thornthwaite method or any other method examined in Chapter 1 by an order of magnitude. For this reason, the $\beta$ factor must be artificially small in GCMs, which means the two variables used to calculate it, atmospheric and surface conductance, must also conform; the atmospheric conductance must always be larger than the surface conductance although, in the real world, there is no such incongruence.

The $\beta$ factor is used in the same manner in the PDSI to estimate evaporation from the potential evapotranspiration except the Thornthwaite method is used (as in the SDDI) instead of the aerodynamic method used in GCMs. Therefore $\beta$ values in PDSI calculations are larger and consistent with field measurements when used correctly; they must be calculated empirically for regions of interest.

In this chapter, the two methods for approximating evaporation for SDDI and soil moisture are manipulated and altered to understand the sensitivity of these water availability measures to changes in formulation.

### 3.1.2 Dependence on previous months’ conditions

The second major difference between the measures is the degree to which they depend on conditions in previous months or their “memory.” It is important to understand how long an extreme event can influence future values of SDDI and soil moisture. The SDDI formulation is a sum of a value generated for the current month’s conditions and the previous month’s SDDI scaled by 0.897. The 0.897-factor was borrowed directly from the PDSI formulation, which was empirically created based on conditions in the Midwest U.S. In GCMs, soil moisture is calculated time step-after-time step and does not require a “memory” factor since soil moisture is by nature cumulative with time. In Chapter 3, SDDI memory is tested by resetting SDDI to zero.
every April and the memories of SDDI, PDSI and soil moisture are evaluated using a time-lag autocorrelation.

3.1.3 The inclusion of additional variables

The final difference in SDDI and soil moisture is the use of variables other than precipitation and potential evapotranspiration. GCM land-surface models generally have multiple soil layers, a variety of land cover types, canopy and bare soil evaporation and condensation as well as sloping surfaces and runoff that remove water from land grid boxes (land-surface model references can be found in Table 1.1). SDDI utilizes no additional variables; the only way for the land to become wetter is through precipitation and the only way the land becomes drier is by evaporation. The calculation of PDSI is slightly more complex. It involves additional variables such as drainage, runoff and even soil moisture.

3.2 Initial SDDI Sensitivity Tests

The decision to use 1928-1978 as the reference period and the Thornthwaite potential evapotranspiration method to calculate SDDI was based on its use in previous studies [Cook et al., 2004]. Before proceeding with a measure comparison, it is essential to identify whether different choices in reference period and potential evapotranspiration method lead to large changes in SDDI. If SDDI is sensitive to one of these changes, the choice will impact projections and should be considered before moving forward.

3.2.1 Sensitivity to reference period

SDDI was calculated using three different reference periods: a 6000 month preindustrial period, 1928 to 1978 as used in the Cook et al. [2004] PDSI analysis and the period from 1950 to 1979 used in the Dai et al. [2004] PDSI analysis. Figure 3.1 shows the 3-year running average of
global mean land-only SDDI from 1901 to 2100 for each of the three reference periods. Calculations using the two 20th century overlapping periods, 1928-1978 and 1950-1979 showed nearly identical results. The SDDI calculated using the 6000-month preindustrial period shows the same patterns just decreased (drier) by approximately 0.3, which indicates that the preindustrial months were slightly wetter than the two 20th century reference periods. The differences between these calculations are small compared to the difference found between SDDI and soil moisture; SDDI should be considered relatively insensitive to reference period. 1928-1978 will continue to be used for this study. It should be noted that differences should be expected if the reference period included years experiencing rapid climate change such as those in the 21st century.

3.2.2 Sensitivity to potential evapotranspiration method

Potential evapotranspiration is evaporation over a wet surface. Therefore, in theory potential evapotranspiration and evaporation should be roughly equal over the ocean (β=1 in Eqn 1.14). There are many methods for calculating potential evapotranspiration that are commonly used today (Chapter 1). The Thornthwaite [1948] method is the default method used to calculate SDDI. It is based on an empirical relationship between potential evapotranspiration and surface air temperature (Eqn. 1.9). Figure 3.2 maps the JJA mean 2081-2100 SDDI calculated using four potential evapotranspiration methods: aerodynamic, Thornthwaite, Hargreaves and Penman.

Globally, the aerodynamic method showed the most severe conditions followed by the Thornthwaite, Penman and finally Hargreaves (also refer to Figure 1.12). The order of SDDI severity using various potential evapotranspiration methods does not align with the actual potential evapotranspiration values because in the actual values, Thornthwaite EP is the least severe (Figure 1.9). The change in EP with climate change appears to be somewhat larger with
Thornthwaite $E_p$ than the other $E_p$ methods with the exception of the aerodynamic $E_p$. Given the SDDI formula, it seems that the change in $E_p$ from the reference period is more important than its absolute value.

The maps in Figure 3.2 show that there are many regions of agreement (i.e. northern South America, northern Africa, southern Europe) even though the potential evapotranspiration methods are very different. Areas of agreement are likely regions in which temperature dominates the potential evapotranspiration calculation since temperature is the common factor for all of the methods (directly for Thornthwaite and Hargreaves and indirectly through the saturation vapor pressure equation for aerodynamic and Penman). Regions of disagreement are most likely areas where a variable other than temperature has a larger influence on the calculation, such as specific humidity or shortwave radiation. These variables as well as many others will be explored on a regional level in Chapter 4.

As Figure 3.2 and Figure 1.12 show, there is quite a range in SDDI projections due to the use of various potential evaporation methods. It is clear that the 21st century global mean SDDI calculated with Hargreaves $E_p$ for the GISS model in Figure 1.12 is closest to the 21st century projections for GISS soil moisture in Figure 2.4. Although the Hargreaves method is desirable for showing projections closest to soil moisture, it is unfeasible for use in this study due to insufficient GCM data in the 20th and 21st centuries.

The aerodynamic method is also undesirable; it is the furthest from soil moisture projections and consistently overestimates observations (Chapter 1). Aerodynamic potential evapotranspiration values are up to 200 times the evaporation over land in some regions because the formulation (Eqns. 1.11 and 1.12) uses the saturation vapor pressure of the ground surface temperature to calculate specific humidity at the ground surface, which is unrealistic over dry
surfaces since surface air temperatures are much higher than they would be over a wet surface with evaporative cooling. However, this test can only go so far. The GCM results for temperature and precipitation arise from the model that uses the aerodynamic formula; it is inherent in all these comparisons. To do a real test, the GCM itself would have to use each of these $E_P$ formulations in its running code, which would also alter its soil moisture.

The Penman method and the Thornthwaite method both show moderate SDDI projections compared to the aerodynamic method. The Thornthwaite method was ultimately chosen for continued use in this study because of its moderate projections and for consistency; it is also the method used in PDSI calculations.

3.2.3 SDDI calculated with inflated Thornthwaite potential evapotranspiration

The Thornthwaite method has been shown to underestimate potential evapotranspiration regionally [Milly, 1994]. Milly [1994] recommends inflating Thornthwaite $E_P$ by 20% to match the upper limits of evaporation (calculated as the difference between observed precipitation and runoff) in the eastern United States. However, when computing SDDI with an inflated Thornthwaite $E_P$ as Milly [1994] suggests, the SDDI projections become drier as shown in Figure 3.3. Since soil moisture shows milder drying than SDDI, making SDDI drier won’t bring it closer to soil moisture. Although scaling Thornthwaite $E_P$ by 1.2 may make potential evapotranspiration a more realistic upper bound to evaporation in the eastern United States, that is not necessarily the case across the globe, particularly in regions with very little surface water. In fact, as shown in Figure 3.3, the regions most prone to desertification, the subtropics, are the regions showing the most severe increase in drying due to the increase in Thornthwaite $E_P$ in SDDI.
3.3 The relative influences of temperature and precipitation on SDDI and soil moisture

SDDI and soil moisture are influenced by temperature and precipitation but it is unclear how much of an influence they each exert. If the changes in soil moisture and SDDI are each approximated as a linear relationship with surface air temperature and precipitation changes, their relative influences can be estimated using a multiple linear regression to solve for the coefficients. Equations 3.1 and 3.2 are the linear approximations for SDDI and soil moisture changes.

\[
\Delta \text{Soil Moisture} = \alpha_T \Delta T + \alpha_{PR} \Delta PR + \zeta \tag{3.1}
\]

\[
\Delta \text{SDDI} = \alpha_T \Delta T + \alpha_{PR} \Delta PR + \zeta \tag{3.2}
\]

where soil moisture, SDDI, surface air temperature (T) and precipitation (PR) are annual time series anomalies from their 1928-1978 averages for the years 1901 to 2000 and \(\alpha_T\) and \(\alpha_{PR}\) are best-fit coefficients. \(\zeta\) represents the inadequacy of the multiple regression linear fits to these two terms. It should be noted that equations 3.1 and 3.2 are rough approximations. From the Clausius-Clapeyron equation, we know \(E_P\) (and thus SDDI) is not a linear function of temperature. Also soil moisture will not be a linear function of temperature or precipitation given the complexity of its influences. The years after 2000 were excluded purposefully to avoid confusion arising from rapid temperature changes.

Table 3.1 lists a comparison of the terms in Equations 3.1 and 3.2 solved for five GCMs for the seven regions that will be the focus of Chapter 4: the southwestern United States, southern Europe, Uruguay, Colombia, eastern China, eastern Siberia and Australia. The \(\alpha_T\) and \(\alpha_{PR}\) coefficients should not be compared directly since the temperature and precipitation anomalies have different means and standard deviations. Instead the individual terms should be compared.
The first column in Table 3.1 is the quotient of the temperature and precipitation terms (Eqn. 3.3). If the quotient is less than 1, precipitation has the largest influence on the SDDI or soil moisture. Otherwise, if the quotient is greater than 1, temperature has the greatest influence.

$$\left\{ \begin{array}{ll}
\frac{\alpha_T \Delta T}{\alpha_{Pr} \Delta Pr} < 1, & \text{Precipitation has the largest influence} \\
= 1, & \text{No difference} \\
> 1, & \text{Temperature has the largest influence}
\end{array} \right. \quad [3.3]$$

The second column of Table 3.1 is the portion of the change in soil moisture (or SDDI) explained by the first two terms in Equations 3.1 and 3.2 and the third column is the portion explained by the third term, $\zeta$. The sum of the second and third columns in Table 3.1 is always one. The final column is the coefficient of determination or the goodness of fit. With a good fit, the value of $\zeta$ should be small relative to the other terms.

From the soil moisture regressions, it is not always clear which water availability measure is more dominant. Only in southern Europe do four out of five models agree that temperature dominates. For the remaining regions there is disagreement. For the SDDI regressions, it is clear that temperature has a much larger influence than precipitation in all regions except eastern Siberia where precipitation dominates (although the $r^2$ values are relatively low) and eastern China where there is disagreement among models.

SDDI and soil moisture receive the same inputs of temperature and precipitation. The difference must be either in how temperature is used to calculate evaporation or an additional term that is not in the SDDI formula such as runoff or recharge. Assuming first that the difference is related to evaporation, the next section explores the relationship between surface air temperature and potential evapotranspiration.
3.4 Dependence of Potential Evapotranspiration on Surface Temperature

The top row of Figure 3.4 shows plots of Thornthwaite and aerodynamic $E_P$ versus surface air temperature. The orange and green dots represent 1971-2000 and 2071-2100 values respectively. Surface air temperatures and their corresponding aerodynamic $E_P$ data were taken from GISS Model ER output. The relationship between temperature and $E_P$ remains the same from the 20th to the 21st century for both Thornthwaite and aerodynamic $E_P$. From the previous multiple linear regression analysis, the relationship between potential evapotranspiration and surface air temperature was found to be much stronger in SDDI than soil moisture. SDDI evaporation is very sensitive to changes in temperature. However, Figure 3.4 shows that the Thornthwaite $E_P$, which is used to calculate SDDI, is less sensitive to changes in surface air temperature than the aerodynamic $E_P$ used in GCMs, which calculate soil moisture.

The actual relationship between GISS evaporation and surface air temperature is much more similar to Thornthwaite $E_P$ and temperature than aerodynamic $E_P$ and temperature (Figure 3.4, bottom left). If it is not $E_P$ that makes SDDI evaporation more sensitive to changes in surface air temperature than soil moisture, it must be another component of evaporation; it must be the scaling factor $\beta$ (Eqn. 1.14), which is the topic of the following section, 3.5.

Looking closer at the behavior of Thornthwaite and aerodynamic $E_P$ in Figure 3.4, there are differences in various temperature regimes. Some of that is because of the Thornthwaite $E_P$ formulation. Thornthwaite $E_P$ is set to the minimum value of zero when the temperature is less than 0°C due to imaginary values arising from the non-integer exponent in its formulation in Equation 1.9. For temperatures above 26.5°C, $E_P$ only depends on temperature, not the annual heat index (I) or m (Eqn. 1.10). $E_P$ values for temperatures higher than 26.5°C are assigned from Figure 13 in *Thornthwaite* [1948].
To evaluate the impact of this upper limit on Thornthwaite $E_P$ and in turn SDDI, we removed the restriction and calculated “unlimited” Thornthwaite $E_P$ at temperatures above 26.5°C in the same way as temperatures between 0°C and 26.5°C. The graph in the bottom right corner of Figure 3.4 shows the unlimited Thornthwaite $E_P$ versus surface air temperature. The average land-only unlimited Thornthwaite $E_P$ is approximately 464 mm/mo in JJA and 247 mm/mo in DJF as opposed to approximately 154 mm/mo and 170 mm/mo for JJA and DJF standard Thornthwaite $E_P$ respectively. The unlimited Thornthwaite $E_P$ still does not approach aerodynamic $E_P$ values for temperatures over 26.5°C. This temperature regime is of particular importance because it represents annual mean conditions in the tropics and subtropics. Figure 3.5 shows the 2071-2100 GISS JJA and DJF mean percentage occurrence of flood or drought according to SDDI relative to 1928-1978 conditions. Areas projecting increasingly fluvial conditions in the tropics in the 21st century SDDI with the standard limited $E_P$ show increasingly dry conditions when the unlimited $E_P$ is used instead. Compared to soil moisture in the right column of Figure 3.5, SDDI with unlimited $E_P$ is too dry. SDDI with the standard limited Thornthwaite $E_P$ and wetter conditions in the tropics is in closer agreement with soil moisture.

### 3.5 The importance of $\beta$ in evaporation calculations

In the GISS model, the evaporation is calculated from the aerodynamic potential evapotranspiration with an efficiency factor, $\beta$ for scaling:

$$ E = \beta E_P $$  \[3.4\]

where

$$ \beta = \frac{C_s}{C_A + C_s} $$  \[3.5\]
CS is the surface conductance (defined in section 3.6) over either bare soil or vegetation and $C_A$ is the atmospheric conductance:

$$ C_A = \rho V_S C_q $$ \[3.6\]

$\rho$ is the density of air, $V_S$ is the surface wind speed and $C_q$ is the turbulent transfer coefficient. The behavior of potential evapotranspiration has been repeatedly evaluated in this study. However the role that $\beta$ plays in SDDI and soil moisture calculations has yet to be examined. Equation 3.4 shows that $\beta$ could be key in 21st century SDDI and soil moisture disparities. To examine the influence of changes in $\beta$, the change in evaporation (Eqn. 3.4) with time is approximated as:

$$ \Delta E \approx \beta_0 (\Delta E_p) + (\Delta \beta) E_{p0} $$ \[3.7\]

where $\beta_0$ and $E_{p0}$ are the 1971-2000 mean scaling factor and potential evapotranspiration respectively. The SDDI formula (Eqn. 1.6) does not include a $\beta$ term to scale the Thornthwaite potential evapotranspiration. So for SDDI, $\beta$ is equal to one and the change in evaporation is simply equal to the change in Thornthwaite potential evapotranspiration. PDSI (Eqn. 1.1) does include $\beta$ but it has the same 12 monthly values each year so the change between the 20th and 21st centuries ($\Delta \beta$) is equal to zero.

As mentioned above, the GISS GCM, which is used to calculate soil moisture does include $\beta$ and it changes with time so both terms in the evaporation change approximation (Eqn. 3.7) stay intact. Figure 3.6 shows evaporation change approximations for the a) SDDI, b) PDSI and c) soil moisture as well as d) the GISS modeled evaporation change (Note: The $\beta$ values were calculated using Equation 3.8. For PDSI, the $\beta_{GCM\ Global}$ term is an array of 12 monthly averages for each gridbox. The $\beta$ ratio in parentheses is an array of 12 monthly averages for the United States. Since PDSI $\beta$ values are only available for the U.S., a global solution was necessary. This
was done by comparing the PDSI and GISS GCM $\beta$ values over the U.S. and then, utilizing the global GISS $\beta$ values, calculating an equivalent PDSI $\beta$ value for the non U.S. locations. The $\beta$ used for soil moisture, $\beta_{\text{GCM Global}}$ was calculated for the GISS model by dividing the evaporation by the aerodynamic $E_P$.

$$\beta_{\text{PDSI Global}} = \left( \frac{\beta_{\text{PDSI US}}}{\beta_{\text{GCM US}}} \right) \beta_{\text{GCM Global}}$$  \[3.8\]

The underlying differences this approximation implies about SDDI, PDSI and GCM (soil moisture) evaporation changes between the end of the 20th and 21st centuries are significant. Figure 3.6 includes four very different images of evaporation change. The difference is $\beta$. In the SDDI and PDSI evaporation change approximations (Figure 3.6a,b), simply introducing a $\beta$ term that is less than one lessens the severity of evaporation projections. However, the change in $\beta$ over time in the GCM greatly impacts the evaporation approximation (Figure 3.6c). Globally, $\beta$ steadily decreases over the 21st century due to increasingly dry global conditions. Decreases in $\beta$ results in a negative change in $\beta$ in Equation 3.7 for the GCM evaporation approximation (Figure 3.6c) and is what leads to the least severe changes in the evaporation approximations. The actual GISS modeled evaporation change (Figure 3.6d) is most similar to the evaporation approximation that included a change in $\beta$ (Figure 3.6c). Since $\beta$ seems to play a significant role in evaporation, perhaps including $\beta$ in SDDI calculations could shed some light on the differences between water availability measures.

### 3.5.1 SDDI with fixed and dynamic $\beta$

There are two ways to introduce $\beta$ to SDDI calculations. As PDSI and the GISS GCM have illustrated, $\beta$ can be “fixed” with 12 monthly values that stay the same from year to year ($\beta_{\text{PDSI Global}}$ as described above) or $\beta$ can be “dynamic” ($\beta_{\text{PDSI Global}}$ if $\beta_{\text{GCM Global}}$ is a timeseries...
from 1901 to 2100 instead of 12 monthly means), changing with each time step. Equation 3.9 is a new SDDI formulation, which can accommodate both a fixed or dynamic $\beta$.

$$SDDI(i) = 0.897SDDI(i-1) + \frac{Pr - \beta EP - (Pr - \beta EP)_{ave}}{\sigma(Pr - \beta EP)} \tag{3.9}$$

An analysis of $\beta$ in various temperature regimes ($<0^\circ C$, $0^\circ C$ to $20^\circ C$, $20^\circ C$ to $26.5^\circ C$, >$26.5^\circ C$, and >$33^\circ C$) during the 2071 to 2100 period has shown that the global mean fixed $\beta$, dynamic $\beta$ and $\beta_{GCM\ GLOBAL}$ (or “GCM $\beta$” used to calculate soil moisture) are all maximum between $0^\circ C$ and $20^\circ C$ and fall off rapidly at lower and high temperatures. At all temperatures, fixed $\beta$ is larger than dynamic $\beta$, which decreases throughout the 21st century. The GCM $\beta$ is always the smallest of the three, which balances out the oversized aerodynamic $E_P$ when multiplied to obtain the GCM evaporation (Eqn. 3.4). Using Equation 3.4, for $0^\circ C$ to $26.5^\circ C$, the SDDI evaporation is largest ($\beta=1$ with Thornthwaite $E_P$) followed by GCM evaporation (GCM $\beta$ and aerodynamic $E_P$), SDDI with fixed $\beta$ evaporation (with Thornthwaite $E_P$) and SDDI with dynamic $\beta$ evaporation (with Thornthwaite $E_P$). Below $0^\circ C$, the average GCM evaporation is larger than the rest in DJF because the Thornthwaite $E_P$ formulation has limitations for temperatures below freezing.

These evaporation differences then directly impact the SDDI calculations. Figure 3.7 shows JJA average conditions at the end of the 21st century relative to the 20th century for SDDI, SDDI with fixed $\beta$, SDDI with dynamic $\beta$ and soil moisture. The results are displayed as the percentage occurrence of drought (negative) or flood (positive) in the 30 year 2071-2100 JJA average relative to the 1971-2000 JJA months. SDDI with fixed beta dampens the influence of the potential evapotranspiration. For the SDDI with dynamic $\beta$, the evaporation was inhibited even
more due to a decreasing trend in $\beta$ over the 21st century. Adding fixed and dynamic $\beta$ has brought SDDI closer to soil moisture.

In fact, in Figure 3.7 SDDI with dynamic $\beta$ exhibits wetter global conditions than soil moisture. Figure 3.8 illustrates how SDDI, SDDI with fixed $\beta$, SDDI with dynamic $\beta$ and soil moisture change over time in the GISS model. The SDDI with fixed beta lies in between the original SDDI and soil moisture. The SDDI with dynamic beta is closer to soil moisture than the original SDDI. It seems that $\beta$ has a large influence on SDDI and helps explain some of the differences between these two water availability measures.

This comparison can be looked at from another angle as well. Table 3.2 shows the number of gridboxes that agree on SDDI and soil moisture conditions. The sum of numbers in Table 3.2 adds up to the number of land gridboxes in the GISS GCM. Numbers to the left of the diagonal indicate that soil moisture is drier than SDDI, those to the right of the diagonal indicate that SDDI is drier than soil moisture and the numbers on the diagonal are the number of gridboxes in which SDDI and soil moisture are in the same range. Tables 3.3 and 3.4 are additional matrices with soil moisture compared to SDDI with fixed and dynamic $\beta$ respectively. SDDI with fixed $\beta$ displays the closest fit with soil moisture. As seen in Figures 3.7 and 3.8, when dynamic $\beta$ is added, SDDI actually becomes wetter than soil moisture.

In JJA, mean 2071-2100 projections of regular SDDI (with $\beta=1$) and SDDI with fixed $\beta$ are drier than soil moisture and SDDI is wetter than soil moisture at all temperatures up to 33°C. Above 33°C, both SDDI with fixed and dynamic $\beta$ are wetter than soil moisture. From 0°C to 26.5°C, SDDI with fixed $\beta$ is the best fit to soil moisture and regular SDDI is the worst. Above 26.5°C, SDDI with dynamic $\beta$ is the worst fit to soil moisture.
In DJF, mean 2071-2100 projections of SDDI with fixed $\beta$ and dynamic $\beta$ are both wetter than soil moisture at temperatures below 0°C and above 33°C. Between 0°C and 33°C, SDDI with dynamic $\beta$ is wetter than soil moisture and regular SDDI and SDDI with fixed $\beta$ are drier than soil moisture. SDDI with fixed $\beta$ is the best fit to soil moisture and regular SDDI is the worst fit at all temperatures except between 0°C and 20°C where SDDI with fixed and dynamic $\beta$ are both a good fit to soil moisture.

Some differences arise when using SDDI calculated with unlimited Thornthwaite $E_P$ for temperatures above 26.5°C. In both JJA and DJF, SDDI calculated with the standard Thornthwaite $E_P$ provides the best fit to soil moisture as opposed to unlimited Thornthwaite $E_P$. In both seasons, using unlimited Thornthwaite $E_P$, SDDI with dynamic $\beta$ remains wetter than soil moisture but SDDI with fixed $\beta$ is drier due to the high values of $E_P$. In DJF, SDDI with dynamic $\beta$ is the best fit to soil moisture and regular SDDI is the worst.

Figure 3.9 is a 1981 to 2000 timeline of GISS modeled soil moisture and observation-driven global mean land-only original SDDI, SDDI with fixed $\beta$, SDDI with dynamic $\beta$, and Dai PDSI. Adding fixed and dynamic $\beta$ does indeed move SDDI toward soil moisture but it also drives SDDI away from what PDSI says is true for the 20th century. PDSI has not only been used for the 20th century. It has additional credibility since it has been used to reconstruct paleoclimate water availability from tree ring variations [Cook et al., 2004]. However, if soil moisture and SDDI with dynamic beta are accepted as the more reliable measures of future water availability, a variable that is often overlooked in the land surface scheme is being trusted. How well is $\beta$ understood?

There are many factors that will influence $\beta$ over the next century that are not well understood today. With warmer temperatures there will be regional shifts in vegetation as well as changes in
plant physiology. It is also still unclear how exactly plants will respond to increases in CO₂.

There is an additional category of uncertainties, perhaps more difficult to predict, human uncertainties. Humans can easily cause changes in $\beta$. Changes in land use patterns as well as growing and shifting populations can all influence $\beta$.

$\beta$ is calculated with surface and atmospheric conductance. As discussed previously, there is reason to suspect that the surface and atmospheric conductance values are not representative of real-world values because of the need for a small $\beta$ to balance the large aerodynamic $E_p$ values. Given the significance of $\beta$ in this study, its representation in GCMs is explored in the GISS AR4 vegetation scheme.

### 3.6 GISS AR4 Vegetation Scheme

The interplay between atmospheric and surface conductance determines the amount of water that moves between the land and atmosphere and ultimately determines quite a bit in a GCM’s hydrologic cycle. A close look at the GISS vegetation scheme revealed non-overlapping values of surface and atmospheric conductance (Figure 3.10). The surface conductance values are always much smaller than atmospheric conductance leading to the vegetation always limiting evapotranspiration. The GISS GCM has extremely low values of $\beta$; average $\beta$ values over land are 0.007 from 1971 to 2000 and 0.004 from 2071 to 2100.

In theory, the atmospheric and surface conductance should be of the same order of magnitude. GISS model surface conductance values have a maximum of about 11 to 12 mm/s. Observations by Kelliher et al. [1995] found maximum bulk surface conductance values to range between 20 and 33 mm/s. $\beta$ values are likely too low because surface conductance are lower than observations (Figure 3.10). In a brute force effort to overcome this difference between the model
and observations, the GISS model was run with the surface conductance value multiplied by three.

By increasing the surface conductance, $\beta$ is increased as well as evaporation. Appropriately, in particularly dry areas, conductance values still do not overlap, even with the increase in surface conductance, but in some regions they now do. In Figure 3.10, the "tripled surface conductance" run values for surface and atmospheric conductance, available for 3 locations, show values overlap in the U.S. Midwest. The surface conductance started at 3 times its initial value and rose to 6 times its initial value within 40 years, which could be due to the increase in soil moisture availability ($\beta_D$) in the GISS surface conductance [Friend and Kiang, 2005; Schmidt et al., 2006]:

$$C_S = \alpha \beta_D f_{\Delta} f_{\text{CO}_2} f_{h} A_{\text{CAP}}$$  \[3.10\]

where $C_S$ is the surface conductance over vegetation, $\alpha$ is a constant of proportionality in [$m^3_H2O/mol^{1}\text{CO}_2$], $\beta_D$ is the soil moisture availability, $f_\Delta$ is the relative effect of atmospheric humidity, $f_{\text{CO}_2}$ is the relative effect of $\text{CO}_2$, $f_h$ is the relative effect of canopy height, and $A_{\text{CAP}}$ is the canopy net photosynthetic capacity.

Precipitation and surface air temperature differences between the original run (1XSC) and the new tripled surface conductance (3XSC) run can be seen in Figure 3.11. The 3XSC run displays a strong decrease in summertime surface air temperatures over land and a small decrease in surface air temperature over land in the winter. Temperatures decrease due to increased evapotranspiration, causing cooling at the surface. Precipitation increases over land in the summer most likely because of the increased atmospheric water from evapotranspiration increases. In both summer and winter there is a southward shift in the ITCZ, due to land temperature decreases in the northern hemisphere. Over bare soil, such as deserts there is no
change because the surface conductance is only over vegetated regions. Any changes over bare soil are due to the inherent differences between model runs and changes in dynamics caused by alterations over vegetated regions.

The 3XSC run also had a strong impact on soil moisture values, which decreased in many regions in both summer and winter seasons because of increased surface conductance (Figure 3.12). Some areas, particularly northern Europe showed a strong increased in soil moisture in the 3XSC run because of increased precipitation and decreased temperatures, which would restrict evaporation. Although most regions show decreased soil moisture in the 3XSC run due to increased evaporation, JJA and DJF SDDI maps in Figure 3.12 show overall increases to wetter conditions globally due to decreased temperatures and increased precipitation. In JJA, the Midwest U.S. shows strong increases in precipitation and decreases in temperature in the 3XSC run compared to the 1XSC run. However, in DJF, precipitation and temperature increases in some parts of the Midwest U.S. and decreases in others. As expected, SDDI shows wetter conditions throughout the region in JJA and DJF, but soil moisture displays a mixed response, partially due to the mixed DJF conditions, in addition to the opposing impacts of having both increased evaporation and precipitation in JJA (Figure 3.12).

An RMS difference analysis between the surface air temperature and precipitation from the 3XSC run with data showed that the 3XSC model run gave more realistic values than the original GISS model run for 20th century surface air temperature in the northern hemisphere all year long and for precipitation during the summer in the northern hemisphere (Table 3.5). If the 3XSC run is indeed more realistic, then temperature and precipitation conditions may be milder than the 1XSC run predicts. However, there is disagreement in the water availability measures’ responses; there is increased drying in soil moisture in the 3XSC run because of the increased
surface conductance and resulting evaporation while SDDI shows wetter conditions due to
decreased temperatures and increased precipitation. The change in surface conductance, by
creating milder SDDI projections and more severe soil moisture projections, shows how one
variable change can bring the two water availability measures closer together.

It should be noted that as CO$_2$ levels rise, the surface conductance will likely decrease.
Increasing atmospheric CO$_2$ frequently causes stomatal closure [Morison, 1998]. Friend and
Kiang [2005] included this behavior in the GISS vegetation scheme in the surface conductance
equation (Eqn. 3.10). They use the following formula for the relative effect of CO$_2$ on surface
conductance from a relationship measured by Forstreuter [1998]:

$$ f_{CO2} = (C_i + 0.004)/5C_i $$

[3.11]

where $C_i$ is the internal leaf CO$_2$. Doubling internal leaf CO$_2$ for the rainforest reduces the
surface conductance by 13% (using $C_i$=0.0113 mol/m$^3$ for the current value in the rainforest
[Friend and Kiang, 2005]), a further departure from the range of atmospheric conductance
values.

### 3.7 Dependence on previous months’ conditions

Certain assumptions have been built in to the SDDI formulation such as its memory. The
dependence on previous months comes from the 0.897-factor, which is borrowed from the PDSI
formulation (Eqns. 1.1 and 1.6). The time dependence of SDDI could explain some of the
difference between soil moisture and SDDI. A longer “memory” can be associated with less
responsiveness to year-to-year atmospheric changes. On the other hand, it is more sensitive to
cumulative changes, like consistent global warming. In order to test the influence of previous
conditions on SDDI, SDDI was set to zero every April. Of course, resetting to zero assumes that
whatever the situation was in the previous summer, synoptic variability is sufficiently large in
winter that everything equals out by spring. The memory is assumed to be less than 6 months. Results showed long-term changes in SDDI in both JJA and DJF (Figure 3.13). The influence of an April change on DJF values shows that SDDI is still affected by previous conditions even after eight months (April to December). This suggests that the time constant needs to be examined.

To further understand the relative “memories” of SDDI, PDSI and soil moisture, an autocorrelation analysis was performed. Each measure was correlated with itself shifted by a specified time step. Figure 3.14 shows the monthly and annual autocorrelation functions for SDDI and soil moisture anomalies from five GCMs in addition to Dai PDSI. Figure 3.14 suggests that the GCM soil moisture does not lose all of its memory for a couple years at least. The ‘six month’ experiment is an exaggeration. Autocorrelation functions for SDDI and soil moisture revealed that SDDI has a stronger “memory” for the first year than soil moisture likely due to 0.897-factor shared with PDSI. Although, MIROC soil moisture stands out as having a strong memory over this period compared to other models because of the extremely high soil moisture values and average variability in MIROC relative to the other models (Figure 1.2). GFDL soil moisture shows the opposite behavior. The annual autocorrelation shows that the long-term memory of the Dai PDSI is more similar to SDDI than soil moisture, particularly CCCMA and GISS SDDI.

An additional comparison of GISS SDDI and soil moisture autocorrelation functions showed that when we altered the surface conductance in the GCM, we also altered the memory of the soil moisture. The 3XSC soil moisture showed a shift to increased “memory.” So in a sense, by changing the surface conductance, soil moisture and SDDI became more similar in an additional way.
3.8 The inclusion of additional variables

There are three variables included in PDSI that are not considered in the SDDI formulation: recharge, runoff and soil moisture loss (Eqn. 1.3). SDDI only includes changes in evaporation and precipitation while soil moisture calculations take into account many more intricate vegetation and land surface interactions. Including runoff or recharge in the SDDI formulation would have an impact on SDDI projections. The impact would be seen regionally since recharge and runoff change with location and season. In Chapter 1, Figure 1.10 shows similar changes in SDDI and PDSI in the 21st century in New York with out any alterations to SDDI. Palmer [1965] tuned the empirically based PDSI formulation to Midwest U.S. soil characteristics, where runoff and recharge magnitudes are small compared with evaporation and precipitation numbers in JJA but larger in DJF.

The soil moisture loss shows up in the PDSI equation as the potential soil moisture loss ($L_P$, Eqn. 3.12) multiplied by a scaling factor (the mean monthly moisture loss divided by the mean monthly potential moisture loss). $L_P$ is defined as the soil moisture loss when there is no precipitation.

$$L_P = \min(E_p, S')$$

where $S'$ is the total soil moisture at the beginning of the month. Although, Palmer [1965] assumed that the available water capacity is fixed at a constant 254 mm over the entire United States so $S'$ would be less than that [Palmer, 1965]. Current GCMs generally have larger water capacities (i.e. deeper soil layers). Interestingly, since the global mean soil moisture change by the year 2100 is relatively small, approximately 0.5 standard deviations from the 1928-1978 average, the fact that SDDI is lacking soil moisture loss in its formulation is likely not felt (Figure 3.8).
Without including additional variables in SDDI, for soil moisture projections to be wetter than SDDI, the SDDI evaporation must be large or soil moisture recharge has to be large. When soil moisture is drier than SDDI, soil moisture runoff must be greater. By not including runoff and recharge terms in the SDDI formula, there is only one scenario in which soil moisture can be drier than SDDI.

3.9 Conclusions

The fact that modeled soil moisture and drought indices project different severities of water availability change over the next century should be a cause for concern in the modeling and climate impacts communities. The discrepancies between soil moisture and SDDI are largely related to differences in evaporation approximations. SDDI has been shown to be sensitive to the chosen method of potential evapotranspiration calculation; SDDI calculated with Hargreaves $E_P$ shows the most similarity to soil moisture. It was shown that for SDDI use, the amount the $E_P$ changes from its reference period is more important than its absolute value; a larger change results in a larger impact on SDDI. An additional SDDI sensitivity test, using multiple regression analysis showed that SDDI is more sensitive to temperature than soil moisture. However, the Thornthwaite $E_P$ used to calculate SDDI is less sensitive to temperature than the aerodynamic $E_P$ used to determine soil moisture.

The scaling factor $\beta$ is the link between $E_P$ and evaporation and it has been found to play a large role in bridging the gap between soil moisture and SDDI projections. $\beta$ limits the amount of moisture that moves between the land and atmosphere. When $\beta$ is added to the SDDI formula, the evaporation is dampened and SDDI becomes more similar to soil moisture. SDDI and soil moisture also become more alike when the surface conductance is increased; soil moisture
displays global mean drying due to increased evaporation and SDDI conditions become wetter due to increased precipitation and decreased temperatures.

Other than differences in evaporation approximations, soil moisture and SDDI differences are also related to their dependence on previous conditions. SDDI and soil moisture both have long-term “memory.” Although, for most models in this study, SDDI is influenced for a longer period by events in the past, which is likely due to the 0.897-factor in its formulation. Synoptic variability in the winter is not strong enough to limit the water availability memory to six months. SDDI, PDSI and soil moisture are influenced for multiple years by previous events. Soil moisture from the increased surface conductance run shows increased memory, closer to SDDI than before.

The final category of differences between the two measures is the inclusion of a multitude of variables in the vegetation and land-surface scheme to calculate the soil moisture, which are not included in the SDDI. PDSI includes three additional terms not in SDDI either: recharge, runoff, and soil moisture loss. The magnitude of runoff is dependent on region and season but it can be comparable to precipitation and evaporation according to IPCC [2007], which could change SDDI calculations if included [Palmer, 1965]. However, soil moisture changes do not represent the same magnitude of change as precipitation or evaporation in the 20th or 21st century projections and would therefore be unlikely to greatly influence SDDI (Figures 2.2 and 2.4).

The two water availability measures can be altered to become more like one another in a number of ways. However this knowledge only leads to another question, “Which one is better?” The most important thing to ask is, “What would make one of them a better choice than the other in a warming climate?” What is expected of the future nature of drought must be considered. Storms are expected to be shorter in duration and more intense according to IPCC AR4. The
GCMs that calculate soil moisture are able to resolve short timescale precipitation events. However, SDDI could not since it uses average monthly precipitation. Both measures reflect changes due to ongoing temperature increases. Two other expected changes are regional shifts in vegetation and changes in stomatal conductance due to increased CO$_2$. GISS as well as many others GCMs are working towards a functional fully coupled dynamic vegetation scheme but they are not there yet. The SDDI remains blind to vegetation.

It is possible that a simple formula like SDDI may be better than a complex land scheme used to calculate soil moisture. More complex parameterizations may differ substantially from reality – the high aerodynamic $E_p$ and low GCM $\beta$ values being just one prominent example. Vegetation and the nature of its change are extremely complicated to assess. The simple measures, as suggested by the relevance of PDSI to observed paleo drought situations (e.g. tree rings) might be able to capture the ‘emergent behavior’ better [Cook et al., 2004].

Ultimately, which measure should we use, SDDI or soil moisture? Since neither measure is perfect, it is important to understand the abilities of each. Since they have different strengths and weaknesses, perhaps the best approach is actually to use both; when they disagree, we can decide which is most appropriate to the situation, and when they agree, the strongest case can be made for a model’s water availability projections.
4  Future Regional Water Availability

4.1  Introduction

The previous three chapters discussed future global projections of water availability and methods of measuring available water. A global discussion is necessary to gain an understanding of average projected changes but discussions of regional projections are the key to realizing the full range of potential impacts on humans and the ecosystems they inhabit. Chapter 4 is focused on the future projections of regional water availability using the same five IPCC AR4 GCMs used in Chapters 1, 2, and 3 (Table 1.1): CCCma CGCM3.1, GFDL CM2.1, GISS Model ER, HadCM3, and MIROC 3.2 midres.

We chose seven regions for closer study: southwestern United States, southern Europe, Uruguay, Colombia, eastern China, eastern Siberia, and Australia (Figures 4.1 and 4.2). Each of the seven regions meet one of three criteria:

1) There is agreement among water availability measures in five GCMs that drought severity will increase in the 21st century.

2) There is uncertainty in water availability changes due to disagreement between GCMs.

3) There is uncertainty in water availability changes due to disagreement between water availability measures.

The regions are scattered across five continents and two hemispheres. They represent climates in the tropics, mid latitudes and high latitudes. Changes in water availability in any of the seven regions would impact large populations. For all but eastern Siberia, this would include the population of the region. Although there are very few people living in eastern Siberia, it is
unique among the seven regions for its potential to impact global climate by releasing methane gas from melting permafrost.

For each region, this chapter summarizes the present day water cycle influences and vulnerabilities and the GCMs’ abilities to match the regional climate. After establishing how well the GCMs capture the 20th century regionally, we examine 21st century projections and discuss potential mechanisms that could cause the modeled water availability changes. Finally, we identify the most likely scenarios and discuss the potential implications. In addition to the seven regions, one additional region, the Middle East is introduced in an abbreviated section and will be the focus of a separate study.

4.2 Southwestern United States

4.2.1 Present Day Water Cycle Influences and Vulnerabilities

The southwestern United States (31.5N to 36.5N, 124W to 101.5W) is an area with a current scarcity of water and a history of battling drought. With the exception of the coast of California and the Rocky Mountains, most of the region shares an arid to semiarid climate. The estimated population in the southwestern U.S. as of 2009 was approximately 56 million with an estimated population growth from 2000 to 2009 ranging from 9.1% to 32.3% by state [U.S. Census Bureau, 2010]. Nevada, Arizona, and Utah have the top three highest population growth rates in the United States. Appropriately, the state economies of the southwestern U.S. have evolved to be somewhat independent of water supplies. Nevada is the exception with tourism and entertainment as the leading industry, which dictates a need for a ready supply of water for visitors.

Water consumption is not likely to stay steady with population increases unless major water conservation projects are successful. The Colorado River, an essential water resource in the
southwestern U.S., is showing warning signs with decreased flow. The Colorado River Basin covers a large portion of the southwestern U.S. Even at current consumption, Lake Mead and Lake Powell, the two major reservoirs in the Colorado River Basin, are in danger of drying up within the next fifty years [Barnett et al., 2008]. Global warming triggered changes in evapotranspiration, precipitation and snowmelt runoff, which supplies a large amount of water to the basin, will play key roles in the future water availability of the region.

Regional energy shortages are a potential threat when levels in Lake Mead and Lake Powell drop. These two lakes provide the majority of hydroelectric power in the region. Without live storage, they will be unable to produce. The southwestern region produces approximately 4,929 thousand MWh of hydroelectric power [Energy Information Administration, 2008]. This represents about 19% of the total hydroelectric production in the United States but only 0.132% of the total energy production in the United States.

During the summer, the southwestern U.S. and northwestern Mexico receive a large portion of their annual precipitation from the North American Monsoon System (NAMS). High summer temperatures create a thermal low over the Mexican Plateau and the deserts in the southwestern U.S. causing wind to flow into the region from the south and east. Thunderstorms develop as warm, moist air is pushed up to higher altitudes in regions such as the Sierra Madre Occidental along the western coast of Mexico and Mogollon Rim in Arizona. The monsoon lasts from July until mid September in the southwestern U.S. but is variable from year to year. Flash floods and lightening are a serious danger during this time. Also, the monsoon has a strong influence on wildfires in the region. Years with heavy rainfall increase soil moisture, which helps to reduce wildfires. However, they also encourage winter plant growth, which can fuel future summer wildfires.
During the winter, ENSO exerts a large influence on drought in the southwestern U.S. with greater (less) rainfall during El Niño (La Niña). Cold water in the equatorial eastern Pacific during La Niña conditions shift the subtropical jet stream north, moving storm tracks to the northwestern U.S. Fewer storms lead to less overall precipitation in the region and greater potential for drought and wildfires. Conversely, El Niño events tend to strengthen the subtropical jet causing an increase in precipitation over the southern U.S. in the winter.

4.2.2 Observed and modeled 20th century climate

All of the models underestimate temperature in the southwestern U.S. although the GCM that comes closest to matching observations in the region is GISS (Figure 4.3). Monthly temperature and precipitation observations for the 20th century are from the CRU TS 2.0 global dataset [Mitchell and Jones, 2005]. The observed temperatures show an increase over the 20th century, which all five models were able to capture.

Figure 4.3 also shows 20th century modeled and observed precipitation. CCCma does a much better job than any of the other GCMs at matching the observed precipitation over the 100-year period. The other models tend to overestimate 20th century precipitation. The GISS and GFDL models not only show the largest overestimation of precipitation in the region but they also display more interdecadal variability than the observations. There are no clear trends for either the GCMs or the observations. However, SDDI calculated with observed temperature and precipitation shows a small trend toward decreasing values (drier conditions) in the 20th century that is matched by all of the models except GISS.

In situ soil moisture measurements are available from the International Soil Moisture Network [ISMN, 2010] for measurements from many stations around the world including some of the regions discussed in this chapter: Australia, Spain, France, Italy, China, and the U.S. (Illinois). There are no measurements available in the southwestern U.S. in this database. However, there
are decades of data down to 2 meters depth from a group of stations in Illinois, which show a slight increase in soil moisture over the last two decades of the 20th century in 9 out of 10 stations. The average 2-meter soil moisture measurement for 1983 to 2000 from 10 stations in Illinois is 766 kg/m² (ranging from 575.9 to 934.2 kg/m²). GCM soil moisture fields are defined to varying depths so it is difficult to do a direct comparison between measurements and models. Keeping that difficulty in mind, meter-per-meter HadCM3 (down to 3m), GISS (down to 3.5m) and MIROC (down to 4m) all underestimate the Illinois soil moisture measurements (Figure 2.22). Soil moisture in GFDL is not defined to a sufficient depth to be comparable and CCCma has variable soil layer depths dependent on land cover. There is no guarantee that any of these models perform the same way over the southwestern U.S. 20th century soil moisture in the southwestern U.S. decreases in all models except CCCma.

Out of the five GCMs, GFDL has been shown to be the most capable of matching observed ENSO amplitude and interdecadal variability, which has influence in this region [AchutaRao and Sperber, 2006; Lin, 2007]. Although GFDL does well modeling ENSO, it consistently overestimated 20th century rainfall and underestimated temperature in the region.

4.2.3 Projected changes in 21st century water availability

4.2.3.1 Boreal Summer

IPCC AR4 multi-model averages show a future decrease in annual precipitation in the southwestern U.S. and a weakening of the North American Monsoon System (NAMS). The NAMS begins in July and is characterized by a shift in seasonal winds from southward in the winter to northward in the summer, which brings rain to the southwestern U.S. [Higgins and Mo, 1997]. An increase in the land-ocean temperature gradient during summer may influence the amplification and northward displacement of the subtropical anticyclone off California, which
could affect the North Pacific eastern boundary current and the strength of upwelling \cite{IPCC2007}. IPCC \cite{IPCC2007} contends that the cooling influence of upwelling waters on SST may dampen precipitation in the southwestern U.S.

According to Figure 4.4, the GCMs in this study are able to capture a southeasterly monsoonal wind pattern in the 1971-2000 JJA mean flow. Two models clearly show increased JJA southeasterly winds from the subtropics at the end of the 21st century: GFDL and HadCM3 (Figure 4.4). Three other conditions are projected that would be expected to enhance the summertime NAMS: 1) JJA high cloud cover over the southwestern U.S. increases in all models, 2) sea level pressure (SLP) decreases in all models except MIROC (Figure 4.4), and 3) there are some areas of increased upward flow in the region (Figure 2.15). Despite increases in southeasterly winds in two models, high cloud cover increases in all models and SLP decreases in four models in the region, all other signs point to a weakening NAMS in agreement with IPCC findings. Figures 4.5 and 2.14 show precipitation decreases in the 21st century. In addition, Figure 4.6 shows decreases in relative humidity. Even if GFDL and HadCM3 do have strengthened conditions for NAMS, increases in evapotranspiration are drying out the area faster than the winds are able to bring moisture into the region.

Both SDDI and soil moisture agree that JJA conditions are projected to be far drier than the mean reference period (1928-1978) conditions by the end of the 21st century (Figure 4.5). There are high temperatures in all of the models in the southwestern U.S. driving increased evapotranspiration. The variations in SDDI are strongly influenced by the increases in temperature.

4.2.3.2 Boreal Winter
In the winter, SDDI and soil moisture projections indicate much drier conditions than mean conditions in 1928-1978 by the end of the 21st century (Figure 4.5). All five GCMs project a strengthening of the subtropical jet stream, which is associated with El Niño events in the 20th century. Westerly winds are intensified and there is an increase in SSTs in the east tropical Pacific Ocean. There is also a strengthening of the Pacific subtropical high in all but one model (HadCM3). However, since high latitude temperature amplification is causing a poleward shift of the polar jet stream and mid latitude lows, storm tracks are displaced poleward and may be out of reach of the strengthening subtropical jet stream. In this way, future El Niño events may strengthen the subtropical jet without contributing to increased precipitation in the southwestern U.S. Three models display an El Niño-like base state change in average tropical Pacific SSTs (CCCma, GFDL and MIROC) with decreased ENSO variability (using the 1%/yr CO₂ increase climate change experiment) [IPCC, 2007]. The poleward shift in storm tracks and the decreased ENSO variability (for CCCma, GFDL and MIROC) could contribute to the projected decreases in 21st century precipitation. HadCM3 displays a La Niña-like base state change and increased ENSO variability, which would be expected to shift the subtropical jet stream poleward and result in decreased precipitation as projected.

The 1971-2000 DJF 200mb to 800mb-mean vertical velocity (∂p/∂t) shows downwelling over the southwestern U.S. in all five models (Figure 2.15) and the DJF global zonal vertical velocity shows downwelling increasing in all five models around 30N to 40N in the 21st century (Figure 2.10). Seager et al. [2007] found modeled mean circulation contributes to decreasing water availability (in terms of precipitation minus evaporation) along the northern edge of the subtropics including parts of the southwestern U.S. An examination of the 21st century changes in vertical velocity in the southwestern U.S. shows some parts do show increased downwelling
but those areas are not geographically consistent between models (Figure 2.15). The drier projections for the southwestern U.S. are not due to a simple Hadley Cell expansion.

4.2.4 Most likely scenario

There is agreement among the GCMs that temperatures will increase, evapotranspiration will increase, precipitation will decrease, soil moisture will decrease, SDDI will decrease, and downwelling will increase in winter (in some areas), which all point to much drier conditions in the southwestern U.S. in JJA and DJF over the next century. Even worse, the GCMs are unable to resolve the high-altitude terrain of the Rocky Mountains, which means the warming due to snow-albedo feedback in that area is likely underestimated. Also runoff water from snowmelt is projected to decrease because the snow depth is likely to decrease [IPCC, 2007]. Using IPCC [2007] probability terminology, there is very high confidence among the five models that the southwestern U.S. will experience a sustained decrease in water availability over the next century.

4.2.5 Potential impacts

In 1922, the seven states in the Colorado Basin (Colorado, New Mexico, Utah, Wyoming, Nevada, Arizona and California) came to an agreement, called the Colorado River Compact, on the allocation of the Colorado River’s water. The agreement was controversial from the beginning. Allotments were disputed. Arizona did not ratify the agreement until 1944. Also in 1944, Mexico was granted a share of the waters as well after a treaty pertaining to water use from the Colorado, Tijuana and Rio Grande Rivers. Future water shortages could be very politically charged when water becomes more limited and must be shared between neighboring states and countries.
Less water for agriculture, threatened ecosystems and a lack of reserved water may lead to, and in some cases already has lead to local conflicts between rural citizens, urban citizens and environmentalists. On the national scale, the Colorado River Basin supplies water to 7 states all with increasing demand. On the international scale, Mexico depends on water from the Rio Grande River and is facing many water shortage problems already.

Since the southwestern U.S. is a region with a history of battling drought, many potential impacts of decreased water availability have already been realized (e.g. water disputes, water shortages, hydroelectric power shortages, water withdrawal limitations for irrigation, increased wildfires and potential for endangered wildlife). However, sustained deepening drought is projected in this region at levels potentially never experienced in the 20th century (Figure 1.5).

4.3 Southern Europe

4.3.1 Present Day Water Cycle Influences and Vulnerabilities

Southern Europe (36.5N to 43.5N, 10.5W to 16.5E) is a region with significant regional climate variability from dry in southeastern Spain to continental in the Alps. Southern Portugal, southwestern Spain, some of France’s southern coast, western Italy and Sicily share a temperate Mediterranean climate with dry summers and warm temperatures. Northern Portugal, northwestern Spain and the rest of France’s southern coast also share a Mediterranean climate but with cooler temperatures. The eastern coast of Italy can be described as humid subtropical with warm temperatures and more precipitation than the Mediterranean regions. The Atlantic Ocean influences the climate of most of France and northern Spain. They receive significant precipitation in all seasons and typically have mild temperatures in what is described as an oceanic climate.
Currently, Italy and Spain can be described as water-stressed based on their Water Exploitation Indices (WEI). The WEI is the total water abstraction divided by the long-term available annual resource, and a country is deemed water-stressed when its WEI is above 20% \cite{European%20Environment%20Agency, 2008}. Spain has the highest water stress in southern Europe with a WEI of 33%. Italy is not far behind with a WEI of 24%, while France and Portugal are close to the water-stress threshold, with WEI values of 18% and 15% respectively. Portugal withdraws more freshwater per capita than Spain or Italy \cite{CIA, 2008}. However, Portugal has approximately 2.5 times more total annual renewable water resources (TARWR) per capita than Spain and about 2 times more than Italy \cite{Water, 2006}. The current problem in Spain and Italy is a lack of sufficient available and renewable water resources.

The economies of southern Europe are heavily dependent on industries that are vulnerable to water risks, with 55% to 70% of southern Europe’s major industries falling into this category \cite{CIA, 2008}. 74% of total annual freshwater withdrawals in France are used for industrial purposes. There are hundreds of water treaties and agreements currently in place between these countries and with other European nations to protect and clarify water rights, particularly with respect to surface waters, which cross or outline borders \cite{Oregon%20State%20University, 2008}. There are additional treaties in effect that concern the sharing of hydroelectric energy, since all three nations are dependent on hydroelectric power generation for a significant fraction of total energy use. Hydroelectric power generation ranges between 14% of the total energy production in France to 31.3% in Portugal.

Agricultural economic dependence on water use are very different across southern Europe. Italy and France rely on agriculture as only a small portion of their GDP with percentages ranging from 2% to 2.2% respectively. 68% of Spain’s total annual freshwater withdrawals are
used for agriculture although agriculture represents only 3.6% of the GDP. In Portugal, agriculture represents a more significant portion of the GDP at approximately 8.2% but also uses a large amount, 78%, of total annual freshwater withdrawals for agriculture [CIA, 2008].

Variations in the wintertime North Atlantic Oscillation (NAO) impact precipitation levels over southern Europe. When the NAO index is positive, there is a stronger than normal subtropical high-pressure center over the Azores and a deeper than usual Icelandic low. During these periods, the large north-south pressure gradient causes westerly winds over the central North Atlantic Ocean to strengthen and stronger and more numerous storms to follow a more northerly track. The northward shift of storm tracks brings additional precipitation to northern Europe and drier conditions to southern Europe [Hurrell and Van Loon, 1997]. When the NAO index is negative, there is a weak subtropical high and a weak Icelandic low. The smaller north-south pressure gradient results in weaker westerly winds over the central Atlantic Ocean and fewer and weaker winter storms flowing eastward. During these periods there are wetter conditions over southern Europe and drier conditions over northern Europe. The NAO has been found to influence water availability not only in winter, but also all year long in southern Europe. Lopez-Moreno and Vicente-Serrano [2008] found significant differences between the standardized precipitation index (SPI) averages for positive and negative wintertime NAO indices and normal conditions during the following spring, summer, and fall seasons. Decreased precipitation in southern Europe due to a positive NAO during winter may have repercussions throughout the following year. The Northern Annular Mode (NAM) is also thought to influence precipitation over Europe by shifting storm tracks poleward away from southern Europe and toward northern Europe in its positive phase.
4.3.2 Observed and modeled 20th century climate

The IPCC AR4 finds that southern Europe has already experienced annual precipitation trends ranging from a 20% decrease to a 20% increase per century between 1901 and 2005, and observed temperature changes ranging from an increase of 0.25°C to 0.55°C per decade between 1979 and 2005 [IPCC, 2007]. Heat waves in southern Europe have received a lot of attention, particularly after the severe heat wave during the summer of 2003, which has been cited as the cause of approximately 20,000 deaths in the region [Met Office, 2008]. The 2003 heat wave was characterized by a number of factors including sustained high temperatures and a lack of precipitation, which led to low soil moisture and reduced evaporative cooling and compounded the heat wave’s severity [Beniston and Diaz, 2004].

Of the five AR4 GCMs used in this study, GFDL comes the closest to the observed CRU TS 2.0 dataset surface air temperatures in southern Europe (Figure 4.7). CCCma and GISS come fairly close but generally underestimate the 20th century temperatures by close to 1°C. HadCM3 underestimates the regional temperature by multiple degrees Celsius. The only GCM that overestimates the temperature is MIROC by over 2°C in some months. Like the observations, all models show an increasing trend in temperature over the 20th century. Figure 4.7 also shows 20th century modeled and observed precipitation. GFDL does the best job matching the observed values. GISS is the biggest outlier for precipitation with 30 mm/mo in excess of observations at many points during the 100-year period. There is no discernable trend over time in the observed or modeled precipitation in the region. However, SDDI calculated with observed temperature and precipitation shows a small trend toward decreasing values in the 20th century that is best matched by HadCM3. The other models show a decreasing trend in SDDI that is about twofold stronger than observations. In situ soil moisture measurements for Spain (18 stations for 2005-
2008 down to 0.05m), France (12 stations for 2007-2010 down to 0.3m) and Italy (2 stations for 2000-2008 down to 0.3m) are available [ISMN, 2010]. However, these depths are not appropriate for comparison with soil moisture from the GCMs, which are an order of magnitude larger. Also, the time period is too short for a comparison of observed and modeled trends. However, all five models show a decreasing trend in soil moisture over southern Europe during the 20th century.

4.3.3 Projected changes in 21st century water availability

The IPCC AR4 found that annual temperatures in Europe are likely to increase more than the global mean [IPCC, 2007]. The multi-model ensemble projects a decrease in precipitation over all of southern Europe in JJA by the last 20 years of the 21st century [IPCC, 2007]. Consistent with this result, Stephenson et al. [2006] examined 15 Coupled Model Intercomparison Project (CMIP2) models with the ability to simulate the NAO pressure dipole and found that 13 predict a shift to a more positive NAO index as CO₂ concentrations increase. In addition, the model simulations show that the snow season is very likely to shorten in all of Europe due to warmer temperatures, and snow depth is likely to decrease in most of Europe, resulting in changes in the seasonality of snowmelt runoff.

4.3.3.1 Boreal Summer

In southern Europe in the summer, there is agreement among water availability measures in the five GCMs studied that drought severity will increase in the 21st century (Figures 4.5, 2.22 and 2.24). There is also a consensus among the models that temperature is increasing and precipitation is decreasing (Figures 4.5, 2.12 and 2.14). Precipitation and relative humidity decrease due to ridging moving poleward over Eurasia (Figure 4.6). In preindustrial times, solar insolation controlled the position of ridging. In the 21st century, with increased CO₂, rising temperature are widespread over land, particularly in the middle of the continent causing ridging
to move poleward in Eurasia. There is no coherent heat source so the warm temperatures do not produce rising but instead result in the thermal expansion of the pressure surfaces.

The precipitation decrease is dampened in Spain and Portugal due to the land-sea temperature contrast. The land in this area is heating up more than the Atlantic Ocean or the Mediterranean Sea. Over Spain and Portugal there is enhanced upwelling and a decrease in SLP. Compared to the rest of Europe, there are much smaller decreases in precipitation and low clouds. Over the Atlantic Ocean near the Strait of Gibraltar, there is increased precipitation due to cool and warm air and ocean currents meeting at the mouth of the Mediterranean Sea.

### 4.3.3.2 Boreal Winter

In the winter there is also agreement between SDDI and soil moisture that conditions are becoming drier by the end of the 21st century in all models (Figures 4.5, 2.22 and 2.24). Temperatures increase and precipitation decreases in all models as well (Figures 4.5, 2.12 and 2.14). The decrease in precipitation can be explained by a positive shift in the Northern Annular Mode (NAM), which should not be confused with the NAMS in the Southwest U.S. A positive shift in NAM results in storm tracks shifting to the north leaving dry conditions in southern Europe and relatively warm and wet conditions in northern Europe.

Our analysis of changes in NAM in the models included an investigation into the contributing factors: sensible heat transport, high latitude warming and the magnitude of tropical warming (Figure 4.8, Table 4.1). Models with reduced northward sensible heat transport at high northern latitudes should have the smallest shift in NAM [Rind et al., 2005]. We also expect models with the smallest shift in NAM to have the smallest high latitude warming and the smallest magnitude of tropical warming. The magnitude of tropical warming is defined as the DJF tropical warming divided by DJF northern hemisphere warming. Taking these three factors into account, we
correctly anticipated the order “NAM-shifting” in the models as defined by mid and high latitude pressure differences (Table 4.1, Figure 4.4). The models with the largest positive shifts in NAM also have the largest precipitation decreases.

4.3.4 Most likely scenarios

There is very high confidence among the five models that Southern Europe will become drier over the next century. There is agreement among the models on increasing temperatures, increasing evapotranspiration, decreasing precipitation, decreases in both water availability measures and a positive shift in NAM that all point to drier conditions in southern Europe in JJA and DJF. It is also likely that conditions are worse than the GCM projections since they are unable to resolve the high-altitude terrain of the Alps, Pyrenees, and Apennines. That means that the warming due to snow-albedo feedback in that area is likely underestimated. Also runoff water from snowmelt is projected to decrease because the snow depth is likely to decrease [IPCC, 2007].

4.3.5 Potential impacts

The annual population growth rate is very low in southern Europe, ranging from 0.01% in Italy to 0.57% in France [CIA, 2008]. If water consumption per capita remains constant, then there will only be a small increase in demand due to population increases. However if precipitation decreases and temperatures rise as predicted, there may be an increase in water demand for irrigation. Optimum conditions for some vegetation may shift northward, potentially affecting the profitability of growing particular plant species in the region [Rosenzweig and Parry, 1994].

According to IPCC WG2 [2007], southern Europe faces reduced water availability, increased drought, severe biodiversity losses, increased forest fires, reduced summer tourism, reduced, suitable cropping areas, increased energy demand in summer, reduced hydropower, increased
land loss in estuaries and deltas, increased salinity and eutrophication of coastal waters, and increased health effects of heat waves.

The countries of southern Europe are all dependent on hydroelectric power generation for a significant fraction of total energy use. If conditions do become drier as projected, then reservoirs run the risk of dropping below a critical level for power generation. Risk of energy shortages, shifts in the agricultural sector and the current industrial interest in maintaining or increasing water resources points to potential future conflicts. There are a number of potential domestic conflicts such as, rural communities resisting the pumping of water to urban communities as well as the use of water to protect endangered species habitats. A larger issue may be international water conflicts. As mentioned, a vast number of water treaties currently exist between the countries of southern Europe. In addition to agreements on water allotments from international rivers, there are also treaty agreements on a variety of issues that may change over the next century including hydroelectric power generation cooperation, water quality and quantity, and flood control and relief. Cooperative agreements between countries may prove difficult when all countries involved are dealing with an unplanned, long-term decrease in water availability.

4.4 Uruguay

4.4.1 Present Day Water Cycle Influences and Vulnerabilities

Uruguay (34S to 29.5S, 59W to 52W) is a small country, approximately 176,220 km² in southeastern South America bordered on the east by Brazil and on the west by Argentina. The climate can be described as humid subtropical. Uruguay receives significant precipitation in all seasons. The annual average rainfall is around 1,182 mm (AQUASTAT, 2008). The austral summer months of January and February are generally the warmest with average temperatures
close to 22°C. The month of June is mild but usually the coldest of the year with averages near 10°C. In the summer, tropical air from Brazil can influence the climate while during the winter, polar air is a periodic influence. Uruguay is particularly vulnerable to rapid changes in weather because of a lack of mountains, which would act as a barrier to storms from the Atlantic Ocean.

Weather variations in Uruguay are generally linked to ENSO, with more precipitation in December, January and February (DJF) during El Niño events. The same phase leads to warmer temperatures in June, July and August (JJA). La Niñas are linked to drier conditions in JJA. The Southern Annular Mode (SAM) is also potentially linked to weather conditions in Uruguay, although the influence is still unclear. Silvestri and Vera [2003] reported negative correlations between the SAM index and precipitation in November and December (late spring) and positive correlations in July and August (late winter). A more recent study by Gillett et al. [2006] was unable to find a robust response.

Uruguay’s current abundance of water has shaped both its public and private sectors. Large dams along the Uruguay and Negro Rivers, designed to generate hydroelectric power, provide 17.3 km³ of storage capacity, approximately 5.5 times Uruguay’s total annual freshwater withdrawal [AQUASTAT, 2008; CIA, 2008]. The CIA estimates that 99.1% of Uruguay’s total energy production is hydroelectric [CIA, 2008], and in 2007, Uruguay exported an estimated 1 billion kWh of electricity [CIA, 2008]. An additional 40,000 km³ of freshwater lies beneath Uruguay, Brazil, Argentina and Paraguay in the Guarani aquifer, one of the largest groundwater reserves in the world [AQUASTAT, 2008]. The World Bank has been involved in the Guarani Aquifer Project to evaluate regional aquifer development and management, promote practical groundwater protection measures at local levels and define an appropriate legal and institutional framework for efficient trans-boundary groundwater management [CIA, 2008].
There are also many smaller dams and reservoirs specifically for industrial and irrigation purposes. The agricultural sector accounts for 96% of annual freshwater withdrawals [CIA, 2008]. However, less than 5% of cultivated land is irrigated [Molden, 2007]. This discrepancy is due to rice cultivation, which accounts for 77% of the total irrigation [Projects, 2008]. Rice is an important crop in the region that requires a great deal of water. The World Bank has been involved in the Natural Resources Management and Irrigation Development Project, which implemented a soil and water management strategy aimed at increasing, diversifying and maintaining agricultural production of individual farmers [Projects, 2008]. Some expected outcomes of this project are the introduction of high-value crops and the implementation of water harvesting at the farm level to help develop an optimal surface water use strategy. In addition to agriculture, most of Uruguay’s major industries depend on a large supply of water. These industries include food processing, electrical machinery, transportation equipment, textiles, chemicals and beverages [Morikawa et al., 2007].

Water treaties with Brazil include an appointment of a joint commission for development of and utilization of natural resources in the Mirim Lagoon, as well as, the use and development of the Cuareim River Basin, which both form the border with Brazil [International Freshwater Treaties Database, 2008]. Water treaties with Argentina include agreements concerning hydroelectric power generation on the rapids in the Uruguay River, which forms the border between the two countries and jurisdiction over navigation in the Plate River. Occasional conflicts have arisen with respect to the use of the Uruguay River [BBC, 2008].

4.4.2 Observed and modeled 20th century climate

The IPCC AR4 reports that Uruguay has experienced an observed warming of 0.05°C to 0.15°C per decade between 1979 and 2005 and an observed increase in annual precipitation ranging
from 20% to 40% per century between 1901 and 2005 [Trenberth et al., 2007]. Of the five AR4 GCMs used in this study, GFDL and HadCM3 come the closest to the observed CRU TS 2.0 dataset surface air temperatures in Uruguay (Figure 4.9). In agreement with the observations, the models all show a slight increase in temperature over the 20th century. GISS overestimates the regional temperature by 3°C in many months.

Figure 4.9 also shows 20th century modeled and observed precipitation. CCCma does the best job matching the observations. GISS is the biggest outlier for precipitation with 75 mm/mo less than the observations at many points during the 100-year period. The observed precipitation shows a larger increase in precipitation than any of the models over the course of the 20th century. There is a similar trend in SDDI; SDDI calculated with observed temperature and precipitation shows a variable but increasing shift to wetter conditions in the 20th century that does not appear in any of the models. Unfortunately, there are no soil moisture measurements available near Uruguay from the International Soil Moisture Network [2010]. However, all five models show an increasing trend in soil moisture over Uruguay during the 20th century.

Out of the five GCMs, GFDL has been shown to be the most capable of matching observed ENSO amplitude and interdecadal variability, which has influence in this region [AchutaRao and Sperber, 2006; Lin, 2007]. Although GFDL does well modeling temperature in Uruguay and ENSO, it consistently underestimated 20th century rainfall in the region.

4.4.3 Projected changes in 21st century water availability

4.4.3.1 Austral Summer

During the summer in Uruguay, all models except GISS show disagreement between projections of SDDI and soil moisture in the late 21st century (Figure 4.5). In the GISS model, both SDDI and soil moisture agree that conditions become drier although SDDI indicates more severe
drying than soil moisture. The relationship between precipitation and SAM index found by Silvestri and Vera [2003] is not present in the 21st century GCM projections with the exception of GISS in DJF. A detailed discussion of SAM projections in the 21st century can be found in section 4.8.

During 20th century, DJF El Niño events have been associated with increased precipitation over Uruguay. The three models that display an El Niño-like base state change in average tropical Pacific SSTs (CCCma, GFDL and MIROC) all show an increase in 21st century precipitation. However, they also display decreased ENSO variability. Future increased precipitation over Uruguay may be associated with mean state changes in these three models. SSTs in the tropical eastern Pacific increase by over 1.8°C in all five models and over 2.4°C in all but GFDL and GISS. The long-term average vertical velocity changes indicate that there are multiple tropical teleconnections (Figure 2.15). There is relative upwelling over the ENSO region in the eastern tropical Pacific Ocean and relative downwelling over northeast Brazil. There is also an alteration in latitudinal bands of vertical velocity and precipitation from the ITCZ southward through the midlatitudes. Vertical velocity in all of the models except HadCM3 is consistent with precipitation patterns. The three models with the El Niño-like base state change in average tropical Pacific SSTs, CCCma, GFDL and MIROC have increased upwelling and precipitation over Uruguay. GISS has downwelling over Uruguay and decreased precipitation. HadCM3 is the exception (increase in precipitation and enhanced downwelling), which is potentially due to having relatively low tropical warming. The source of moisture for the increased precipitation is likely from the high-pressure system off the coast in the Atlantic moving moist air over Uruguay in all models and strengthened by a continental low pressure system in CCCma, HadCM3, and MIROC. The disagreement between soil moisture and SDDI in
this region is most likely due to precipitation having a larger influence on soil moisture than SDDI.

4.4.3.2 *Austral Winter*

During winter in Uruguay, 21\textsuperscript{st} century projections show increased temperature, decreased precipitation and agreement in SDDI among all models that conditions become drier (Figure 4.5). Soil moisture projections show disagreement among models. CCCma and MIROC indicate a shift to increased soil moisture. For CCCma, closer inspection shows that the soil moisture is increasing because of precipitation increases in the south. The decreased precipitation in the north causes the regional average to be negative. However, the regional soil moisture average is evidently sensitive to the southern precipitation decrease. In MIROC, the reason for increased soil moisture is accumulation from wetter seasons. Looking closer at all the models it seems that the annual soil moisture minimum lags the wintertime precipitation minimum by one to three months.

The decreased regional precipitation is due to increased stability over Uruguay in all of the models at the end of the 21\textsuperscript{st} century. SLP increases and the subtropical jet stream is strengthened causing storm tracks to move southward over Argentina. Although precipitation decreases, there are increases in relative and specific humidity over Uruguay. Continental low pressure combined with high-pressure systems to the south and east of Uruguay (Figure 4.4) allows moist air to flow over the region from the Atlantic Ocean.

HadCM3 displays a La Niña-like base state change in average tropical Pacific SSTs with increased ENSO variability and decreased precipitation, which is currently associated with La Niña events in JJA. Future changes in precipitation over Uruguay may be associated with both mean state and variability changes in HadCM3.
4.4.4 Most likely scenarios

Unlike the southwestern U.S. and southern Europe, Uruguay does not show agreement among models on 21st century changes in water availability. It seems likely that Uruguay will continue to be influenced in DJF by tropical teleconnections, which are associated with increased precipitation during El Niño periods. The moist air is likely moved over Uruguay by the high-pressure system off the coast in the Atlantic Ocean. Conditions may be wetter than projected by the models that underestimated precipitation and increasing trends in 20th century precipitation and SDDI. The models that are likely to be the best estimate of future water availability in DJF are CCCma for being able to match observed precipitation and GFDL for its ability to match observed ENSO patterns (Figure 4.9). There is medium to high confidence among the five models that Uruguay in DJF will experience drier conditions over the next century.

In JJA, temperatures are projected to increase and precipitation is projected to decrease. The precipitation decrease is likely due to increased atmospheric stability and a poleward shift in storm tracks away from the region. SDDI and soil moisture show disagreement among models. However, it seems likely that the increased soil moisture in CCCma and MIROC are anomalous and the precipitation is underestimated in most of the models. There is high confidence among the five models that Uruguay in JJA will experience drying over the next century.

4.4.5 Potential impacts

Uruguay is strongly dependent on water, which has not been a problem thus far since the region has an abundance of it. The biggest threats to Uruguay lie in agriculture, sea level rise, storm surges, tourism, the export industry, and potential conflicts over aquifer rights. Hydroelectric power and water-intensive crops such as rice make up a significant portion of Uruguay’s exports and could impact their economy if compromised. Also, as global water availability becomes
more strained, a source of potential conflict is water rights to the Guarani aquifer, which is a huge asset for Uruguay and three other surrounding countries.

Another potential problem for Uruguay is agricultural. A study by Fernandes et al. [2004] found that the incidence of Fusarium head blight in wheat crops will likely increase with climate change in Uruguay. In some cases, problems are easily overcome. For example, by changing the planting dates and additional irrigation, the negative effects of climate change on maize and soybeans can be overcome in Uruguay [Travasso et al., 2006]. However, the increased energy needed for pumping from falling watertables will likely make irrigation more expensive [Maza et al., 2001].

Uruguay is also vulnerable to sea level rise and storm surges along low-lying areas [IPCC WG2, 2007]. Any damage or land loss around the coast or wetlands could disrupt or dismantle ecosystems. It could also seriously damage the tourism industry [Nagy et al., 2006a; Nagy et al., 2006b].

4.5 Colombia

4.5.1 Present Day Water Cycle Influences and Vulnerabilities

Colombia (2S to 10N, 81W to 71W) is in northwestern South America with coasts on the Pacific Ocean and the Caribbean Sea on either side of its border with Panama. Colombia is approximately 1,138,910 km² and borders 4 nations in South America: Venezuela, Brazil, Peru and Ecuador. The climate varies a great deal from region-to-region due to large changes in altitude and influences from surrounding bodies of water. The Andes occupy a large fraction of land in Colombia and reach elevations of over 5,500 m. The climate in the high altitudes is temperate with at least 4 months of the year averaging temperatures above 10°C and the warmest month of the year below 22°C. The mountains in the western part of Colombia are generally
lower in elevation and experience a milder climate, which is similar to the Caribbean coastal region. There they have a climate with warmer tropical temperatures and a pronounced dry season. With the exception of the Guajira Desert in northern Colombia, the remainder of Colombia has a tropical rain forest climate with high rainfall and temperatures with no natural seasons.

Climate in Colombia is intimately tied to ENSO patterns. El Niño is associated with low rainfall and discharges, and La Niña is strongly associated with higher precipitation and streamflows [Poveda and Mesa, 1997]. The precipitation response over Colombia is opposite to the response over the eastern tropical Pacific. Warming in the eastern Pacific during El Niño events act as a Rossby wave source, which produces anomalies in the global circulation. These anomalies are linked to above average surface pressure over tropical South America, which suppresses convection and precipitation in the region and contributes to the drier than normal conditions.

While Colombia’s total annual renewable water resources (TARWR) are abundant, totaling about 200 times its annual freshwater withdrawals [Molden, 2007], it has minimal infrastructure in place for water storage. As of 2000, Colombia had only 9.1 km$^3$ of reservoir storage, less than the annual freshwater withdrawals of 10.71 km$^3$ [AQUASTAT, 2008]. Due primarily to the vast amount of available water, Colombia has become heavily dependent on hydroelectric power generation. Hydroelectric power accounts for 72.7% of Colombia’s total energy production, and in 2005, Colombia exported 1.758 billion KWh of electricity [CIA, 2008]. Many of Colombia’s major industries are also dependent on a large quantity of water or are vulnerable to changes in water availability [Morikawa, 2007].
Agriculture officially accounts for only 11.5% Colombia’s GDP [CIA, 2008]. However, that figure does not include profits from illegal drug trade. As of 2006, an estimated 62% of world cocaine production came from Colombia. With approximately 78,000 hectares of coca plants valued at US$13,039/hectare for cocaine hydrochloride, the cocaine grown each year in Colombia has an estimated worth of over a billion US dollars [United Nations, 2007]. In addition to coca, Colombia is also known to grow cannabis and opium poppies.

4.5.2 Observed and modeled 20th century climate

According to the IPCC AR4, Colombia has warmed between 0.05° to 0.25°C per decade between 1979 and 2005. Between 1979 and 2005, precipitation ranges from increases of 15% per decade along the Pacific coast to decreases of 15% per decade in the interior mountains [Trenberth et al., 2007]. Of the five AR4 GCMs used in this study, CCCma comes the closest to the observed CRU TS 2.0 dataset surface air temperatures in western Colombia and HadCM3 comes the closest in eastern Colombia (Figure 4.10). Temperatures are higher in the eastern half of Colombia than the western half in the 20th century, although CCCma does not show very much differentiation and MIROC has warmer temperatures in western Colombia. The models and observations agree on the increasing trend in temperatures over the course of the 20th century. In eastern and western Colombia, the models also agree with decrease in SDDI calculated with observed temperature and precipitation in the 20th century.

Figure 4.10 also shows 20th century modeled and observed precipitation, which show no obvious trends. Precipitation is higher in western Colombia than eastern Colombia, which is captured in all five of the models. GISS and CCCma do the best jobs matching the observed precipitation in western Colombia and GISS does the best job in the eastern half. Unfortunately, there are no soil moisture measurements available near Colombia from the International Soil Moisture Network [2010].
However, all five models show a decreasing trend in soil moisture over Colombia (except HadCM3) during the 20th century.

As mentioned in the previous section, GFDL has been shown to be the most capable of matching observed ENSO amplitude and interdecadal variability, which also influences this region [AchutaRao and Sperber, 2006; Lin, 2007]. Although GFDL does well modeling ENSO, it consistently underestimated 20th century precipitation and overestimated temperature in both eastern and western Colombia.

4.5.3 Projected changes in 21st century water availability

The IPCC AR4 A1B scenario multi-model ensemble for the precipitation changes from 1980-1999 to 2080-2099 indicate that the there will be increases in precipitation in southwestern Colombia in all seasons and drying in the north annually, particularly during JJA [IPCC, 2007]. There is very little agreement among models in this region. Colombia’s southwestern half shows higher, although unimpressive agreement among models than the northeastern half, with more than 8 models out of 21 agreeing in all seasons [IPCC, 2007].

4.5.3.1 June, July and August

In the five GCMs, modeled JJA conditions at the end of the 21st century show a suppression of the current precipitation patterns in Colombia. The east is normally wetter in this season. While projections for western Colombia indicate decreased precipitation, there is an even stronger decrease in eastern Colombia (Figure 4.11). Soil moisture and SDDI projections agree that conditions in eastern Colombia become drier although the conditions are more severe in the SDDI projections. In western Colombia, SDDI and soil moisture also agree that conditions are projected to be drier in all models except GISS, which projects wetter conditions and HadCM3, which projects a slight increase in soil moisture. GISS agrees with the other models dynamically.
but the difference is that the vertical velocity and precipitation patterns are shifted to the northeast (Figures 2.15 and 2.14). In the GISS model, there is increased precipitation and upwelling across all of Colombia and downwelling to the north over the Caribbean Sea. In the HadCM3 model, the increased soil moisture is due to a local increase in precipitation just along the western coast. SDDI also shows wetter conditions along the western shore in the HadCM3 model.

The suppressed precipitation patterns in all of the models can be explained by a weakening of the tropical circulation cell. The eastern Pacific Ocean cold water warms up but the rising air from the warming ocean competes with the JJA solar insolation peak at 23.5°N thus weakening the circulation cell. During 20th century, El Niño events have been associated with decreased precipitation over Colombia. The three models that display an El Niño-like base state change in average tropical Pacific SSTs (CCCma, GFDL and MIROC) all show a decrease in 21st century precipitation. However, they also display decreased ENSO variability. Future decreased precipitation over Colombia may be associated with mean state changes in these three models. HadCM3 displays a La Niña-like base state change with increased ENSO variability but does not show future increases in precipitation, which are currently associated with La Niña events. Future ENSO mean state and variability changes in HadCM3 seem to be unrelated to future precipitation changes in Colombia unless they act to dampen precipitation decreases.

4.5.3.2 December, January, February

At the end of the 21st century, December, January and February in Colombia, model projections show an enhancement of the current precipitation patterns. However, the one model that displays a La Niña-like base state change in average tropical Pacific SSTs in the 21st century, HadCM3 does not display an expected increase in precipitation. Currently, in DJF the west coast receives
much more precipitation than the eastern region. Projections show increased precipitation in the west and decreased or small changes in precipitation in the east (Figure 4.11). In eastern Colombia, SDDI and soil moisture are in agreement that conditions become drier in the 21st century although they do not agree on the severity. In western Colombia, SDDI projections indicate drier conditions (with the exception of GISS) and soil moisture projects increases in all models (with the exception of HadCM3) (Figure 4.11).

The change in precipitation may be due to the tropical global warming effect. Eastern Pacific cold water warms up. The combination of rising air from the warming ocean and the DJF solar insolation energy peak at 23.5°S cause a strengthening of the tropical circulation cells (Figure 2.15). This is the likely cause for the enhancement of the current precipitation pattern in the region. The ENSO teleconnections discussed for JJA may hold for eastern Colombia in DJF but western Colombia seems to be primarily influenced by the tropical global warming effect.

4.5.4 Most likely scenarios

In JJA, the most likely scenario for Colombia is a suppression of the current precipitation patterns due to a weakening of the tropical circulation cell. In addition, it seems likely that Colombia will continue to be influenced in JJA by ENSO teleconnections, which are associated with decreased precipitation during El Niño periods. In JJA, there is medium to high confidence that western Colombia will experience drier conditions and very high confidence that eastern Colombia will experience drier conditions. However, the uncertainty in projected ENSO changes remains high and will impact these findings.

In DJF, there will likely be an enhancement of the current precipitation pattern with increased precipitation in the west due to a strengthening of the tropical circulation cell. Western Colombia shows opposing projections for SDDI and soil moisture. The fact that GFDL, HadCM3 and
MIROC all underestimated 20th century precipitation gives reason to think that 21st century precipitation may be underestimated by these models as well. However, there is good 20th century agreement between modeled SDDI and SDDI calculated with observed temperature and precipitation in this region. There is medium confidence among the five models that western Colombia in DJF will experience drier conditions. On the other hand, there is very high confidence that eastern Colombia will face continued drying in DJF.

4.5.5 Potential impacts

Colombia is dependent on an abundance of water for energy, industry and agriculture. Yet there is very little infrastructure in place to provide relief in the case of water shortages. It is not likely that increases in population will be a strain on future water supplies [CIA, 2008]. However, decreases in total annual renewable water resources due to decreases in precipitation could change everything. The largest potential economic loss is to the export industry, with losses in hydroelectric power exports and agricultural products. Changes in water availability could even affect the world drug trade if Colombia is no longer able to continue producing at the same volume.

Colombia is also vulnerable to glacier reduction and rises in sea level. Since the end of the Small Ice Age (1850), Colombia has seen an 82% reduction in its glaciers [NC-Colombia, 2001]. Field measurements between 1990 and 2000 show a linear withdrawal of the ice ranging between 10 to 15 m/yr. Current trends point to Colombia’s glaciers disappearing within the next 100 years [NC-Colombia, 2001]. The reduction in glaciers may affect water supply and ecosystem functioning in the high elevations of Colombia between the upper forest line and the permanent snow line, the páramos [IDEAM, 2004]. According to a study by Vásquez [2004], the disappearance of the Colombian glaciers would impact the water supply for 60% of the
population of Peru. In addition, the glacier reduction would impact hydroelectric power production in Colombia and Peru [IDEAM, 2004]. Colombia could also be impacted by rises in sea level. A 1-meter rise could cause permanent flooding of 4,900 km$^2$ of land along the coast and would impact around 1.4 million people [NC-Colombia, 2001]. This level of flooding would inundate 7.2 Mha of crops and pasture and threaten over 44% of the coastal road network.

The current lack of water treaties between Colombia and any of its neighboring countries puts Colombia at high risk for potential water conflicts. Even if conditions stay unchanged, there are good reasons to form agreements with neighboring nations concerning any shared natural resource.

### 4.6 Eastern China

#### 4.6.1 Present Day Water Cycle Influences and Vulnerabilities

Eastern China (21N to 37.5N, 112E to 121E) is defined as the Chinese provinces east of Tibet and south of Inner Mongolia. The climate in eastern China can be described as humid subtropical. Average monthly temperatures are generally above 10°C at least 4 months of the year and the warmest month reaches temperatures above 22°C.

The Asian Monsoon heavily influences eastern China’s climate. It is characterized by a warm, wet summer monsoon and a cold, dry winter monsoon. During the summer months, warm temperatures over the continent create a low-pressure region at the surface, which brings warm, moist winds from the Indian Ocean and South China Sea, creating optimal conditions for heavy rainfall in eastern China. They receive much greater rain in summer than winter, although this is not as true near the coast, which receives significant rain in winter as well. Precipitation observations have shown no clear trends on a national level [IPCC, 2007]. However, there has been a summertime pattern of increased rainfall in the southeast and decreased rainfall in the
northeast, often called the “southern flood and northern drought” pattern. This pattern has caused extensive and severe flooding in the Yangtze River valley, droughts in the north, and drying up of the Yellow River. These changes in precipitation are linked to a weakening trend in the East Asian summer monsoon since the 1920s [Allan and Ansell, 2006], consistent with a tendency for a southward shift in the summer rain belt over eastern China [Zhai et al., 2004]. The monsoonal changes in turn have been related to SST variations in the eastern tropical Pacific and the tropical Indian Ocean [Gong and Ho, 2002] and potentially upper tropospheric/lower stratospheric cooling. Yu et al. [2004] suggest that an upper tropospheric cooling trend during July and August downstream of the Tibetan Plateau, potentially linked with stratospheric anomalies, causes a southward shift in the upper-level westerly jet over eastern China, which leads to observed increases in precipitation over southeastern China (Yangtze River Valley) and decreases in precipitation north of the jet, over northeastern China.

ENSO also impacts this region. The influence of ENSO on the East Asian monsoon circulation is a subject of numerous recent studies [Chang, 2004]. The link between the East Asian Summer Monsoon System and ENSO involves changes in the evolution of the northwestern Pacific subtropical high over the Philippines Sea [Lau et al., 2006; McBride et al., 2003; Wittenberg et al., 2006]. During El Niño winters, northeasterly winds are generally weakened due to a strong positive anomaly in the northwestern Pacific high. This results in a suppressed winter monsoon over East Asia and above average temperatures and precipitation. During El Niño summers, the summer monsoon trough over the western Pacific is typically amplified, which results in increased summertime precipitation. La Niña events tend to have the opposite influence on northwestern Pacific high anomalies [Lau et al., 2006; Chang, 2004].
The influence of ENSO in the western Pacific also extends to tropical storms, although it should be noted that currently GCMs are unable to resolve tropical storms or cyclones. Camargo and Sobel [2004] found that in El Niño years, tropical cyclones are more intense and tend to be longer in duration than in La Niña years. However, there are a greater number of tropical cyclone landfalls in China during the autumn months of La Niña years related to a westward shift in the mean genesis position. El Niño years experience fewer landfalls in autumn due to an eastward shift in the mean tropical cyclone genesis position [Wu et al., 2004]. Between June and November of strong El Niño years, in the region of the northwestern Pacific high, tropical storm numbers are below normal [Wang and Chan, 2002]. During the same time, increases in tropical storm numbers are observed in the southeastern portion of the western North Pacific (0N-17N, 140E-180E). Wang and Chan [2002] found that El Niño-induced equatorial westerlies increase the shear vorticity in the southeastern region, which aid tropical storm formation. In the northwestern region, tropical storm formation is suppressed during El Niño years due to the enhanced northwestern Pacific high and the lowered East Asian trough causing upper-level convergence. Recent years have seen many changes in tropical storm and typhoon characteristics. In the western Pacific, the number of category 4 and 5 tropical storms is approximately 36% higher for the years 1990-2004 than the years 1975-1989 [Webster, 2005]. In 2004, the number of typhoons (21) was well above the 1971-2000 median (17.5) [Trenberth et al., 2007].

China’s water infrastructure is important when considering how vulnerable eastern China is to flooding and droughts. In general this region has abundant water resources. As of 2005, China’s total annual renewable water resources (TARWR) were approximately 2,830 km$^3$ per year, of which only about 19% (550 km$^3$ per year) was used [Water, 2006]. China has the ability to store
approximately 634.5 km$^3$ of water in approximately 85,412 reservoirs [Statistics, 2007]. However, only 59.45% of the reservoirs are up to safety standards. Fortunately 90.2% of the large reservoirs (76.2% of the total national storage) passed safety standards. Domestic, industrial and agricultural freshwater withdrawals are approximately 7%, 26% and 68% respectively [CIA, 2007]. The agricultural sector uses a large percentage of the freshwater supplies, due in large part to the fact that between 15% and 40% of cultivated land in China is currently irrigated. The two main crops, rice and cotton, require enormous freshwater withdrawals [Molden, 2007; CIA, 2008]. Agriculture accounts for a significant portion of China’s GDP at 11.3%. Although industrial water use accounts for only 26% of the fresh water withdrawals, almost all of China’s top industries are considered intensive water use industries [Morikawa et al., 2007]. A change in water availability could impact China economically through agriculture and major industries.

China has recently invested heavily in and become dependent on hydroelectric power generation, which requires the maintenance of minimum water levels. Total hydroelectric output in 2007 was approximately 602,360 thousand MWh, which represents about 18.5% of China’s total power production [CIA, 2008]. With the construction of the Three Gorges Dam, the largest hydroelectric power station in the world, China will add 22,500 MW to its generating capacity, representing an annual energy generation capacity of more than 100 billion kWh when fully operational [CTGPC, 2009].

4.6.2 Observed and modeled 20$^{th}$ century climate

Observed temperatures have increased in eastern China in recent years at a rate of between 0.15°C to 0.55°C per decade between 1979 and 2005 [Trenberth et al., 2007]. Of the five AR4 GCMs used in this study, HadCM3 comes the closest to the observed CRU TS 2.0 dataset
surface air temperatures in eastern China (Figure 4.12). MIROC is the only GCM to overestimate the temperature in this region. The only model that shows a warming trend in the 20th century is CCCma. This upward trend is not obvious in the observations. Figure 4.12 also shows 20th century modeled and observed precipitation. GFDL does the best job matching the observed values. Excluding GFDL, the GCMs tend to overestimate the precipitation in eastern China in the 20th century. GISS is the biggest outlier for precipitation with 70 mm/mo in excess of observations at many points during the 100-year period. MIROC and HadCM3 display a downward trend that is not seen in the observations.

There are no trends in the SDDI from the 20th century GCM runs and the SDDI calculated with observed temperature and precipitation. In situ soil moisture measurements for China are available to a depth of 1 meter between 1981 and 1999 [ISMN, 2010]. The average 1-meter soil moisture measurement for 1981 to 1999 from 5 stations in eastern China is 330.78 kg/m² (ranging from 288.46 to 379.84 kg/m²). Three out of the five stations show a decrease in soil moisture over this period while all but one GCM (MIROC) found show soil moisture decreasing over the 20th century in this region. To compare with GCM soil moisture, the measurements would need to reach 3 to 4 meters in depth. However, a meter-by-meter comparison over eastern China shows that MIROC overestimates soil moisture, HadCM3 is a good match, and GISS underestimates it.

As mentioned in the previous sections, GFDL has been shown to be the most capable of matching observed ENSO amplitude and interdecadal variability, which also influences this region [AchutaRao and Sperber, 2006; Lin, 2007]. GFDL does well modeling 20th century precipitation and temperature as well as ENSO in eastern China (Figure 4.12).

4.6.3 Projected changes in 21st century water availability
IPCC AR4 models suggest that global warming will alter China’s land-sea temperature contrast, weakening the winter monsoon and strengthening the summer monsoon [Kimoto, 2005]. The IPCC AR4 A1B scenario multi-model ensemble for the precipitation changes from 1980-1999 to 2080-2099 indicates that China will experience increasing annual precipitation between 0% and 20%. In the boreal winter, precipitation changes range from a 5% decrease in southeastern China up to a 50% increase in northeastern China, in what appears to be a modification or possible suppression of the “southern flood and northern drought” pattern. In the summer, precipitation predictions range between a 0% and 15% increase, and no north-south pattern arises [IPCC, 2007].

Monsoon circulation patterns are expected to change due to global warming-induced changes in land-sea temperature contrast during the winter and summer. The contrast is reduced in the winter and increased during the summer, which would tend to weaken the winter monsoon and strengthen the summer monsoon. A study using output from IPCC AR4 models to investigate future changes in East Asian circulation confirms this logic and finds a suppressed winter monsoon and enhanced summer monsoon in the 21st century [Kimoto, 2005].

The future influence of ENSO on the climate of eastern China remains to be determined. IPCC AR4 models show very little consistency in tropical storm changes in the western Pacific, likely due to inconsistencies in ENSO. Higher resolution models project increases in precipitation intensity due to future tropical cyclones. Some of these models also project increases in tropical storm peak wind intensities.

4.6.3.1 Boreal Summer

By the end of the 21st century in eastern China, the five models disagree in many respects in JJA (Figure 4.5). Each model falls into one of three scenarios. First, the most common situation,
which occurs in three of the five models, GISS, CCCma and HadCM3 is a suppression of current patterns. In these models, there is a precipitation maximum in northern China and less precipitation and more downwelling in southern China. In this situation, the warming of the continent to the north pulls the monsoon northward.

The second situation applies only to GFDL where the current patterns are enhanced. Precipitation increases across eastern and southern China and decreases along the northeastern coast. There is great warming to the west of the Asian continent and a corresponding region of low pressure, which brings warm, moist air northward from Southeast Asia to southern and eastern China. A high-pressure system to the north of China brings moist air over southeastern China, increasing specific humidity. Increased specific humidity and upwelling in the region allow precipitation increases despite stability.

The third situation involves the only remaining model. In MIROC, changes in vertical velocity align with changes in precipitation (Figure 2.15). In regions of increased upwelling (Tibetan Plateau and off the east coast of China), there is increased precipitation. While in central and eastern China, the decreased upwelling causes decreased precipitation.

In general, soil moisture projections show conditions becoming wetter in all but one model (MIROC; Figure 4.5). However, in the MIROC model, both SDDI and soil moisture agree that conditions become drier. There is agreement between soil moisture and SDDI in all but one model, GFDL. In GFDL, the reason for the strong drying in SDDI is because of a strong temperature increase in southeastern China that does not extend over the entire region. The high regional temperature influenced the average SDDI.

In HadCM3, the precipitation shows basically no change but looking at the map, we can see that in central eastern China, precipitation is decreased and SDDI and soil moisture show drier
conditions (Figures 2.22 and 2.24). To the north and south of this region precipitation increases and SDDI and soil moisture show wetter conditions. The precipitation averages out close to zero while the SDDI and soil moisture still show wetter conditions averaged over the region.

During 20th century, JJA El Niño events have been associated with amplification of the summer monsoon resulting in increased precipitation over eastern China. Of the three models that display an El Niño-like base state change in average tropical Pacific SSTs and decreased ENSO variability (CCCma, GFDL and MIROC), two (CCCma and GFDL) show an increase in JJA 21st century precipitation. HadCM3 has a La Niña-like base state change in the 21st century and increased ENSO variability, which would be expected to produce decreased precipitation in JJA [IPCC, 2007]. However, HadCM3 shows virtually no change in JJA precipitation. Future precipitation changes over eastern China are not obviously linked to the modeled influence of ENSO shifts on the East Asian Monsoon. However, this may change as GCMs improve.

4.6.3.2 Boreal Winter

DJF in eastern China at the end of the 21st century shows agreement among the models that surface air temperatures increase but there is some disagreement about precipitation (Figure 4.5). GFDL and MIROC are the only two models with decreased precipitation. They are also the two with the largest positive shifts in NAM (Figure 4.8). In these models the low pressure does not extend as far to the east over Asia as in the other models. The westerlies have been shifted poleward due to increased positive phase of the NAM causing storm tracks and precipitation to shift to the north as well. The models with smaller NAM shifts (GISS and HadCM3) have increased precipitation. In GISS and HadCM3, the flow extends east without problems allowing for increased precipitation.
During 20th century, DJF El Niño events have been associated with increased precipitation over eastern China due to a suppression of the dry winter monsoon by a positive anomaly in the northwestern Pacific high. Of the three models that display an El Niño-like base state change in average tropical Pacific SSTs (CCCma, GFDL and MIROC) only one (CCCma) shows an increase in DJF 21st century precipitation. Future precipitation changes over eastern China may be influenced more by the decreased ENSO variability in CCCma, GFDL and MIROC than with mean state changes.

4.6.4 Most likely scenarios

The most likely scenario in JJA is a suppression of the current “southern flood northern drought” pattern due to continental warming pulling the monsoonal rainfall northward. Northeastern China is likely to become wetter in this season and southeastern China will either see no change or a shift to slightly more fluvial conditions. There is medium to high confidence among the five models that eastern China, as a whole in JJA will experience more fluvial conditions.

In DJF, a poleward shift of storm tracks away from the region due to a positive shift in NAM is a likely scenario. GFDL and MIROC are the two models that did the best job matching 20th century precipitation in eastern China (Figure 4.13) and they are also the models with the largest shift in NAM. If 20th century behavior holds in the 21st century, precipitation increases in the other models are likely overestimated and eastern China will see mild changes in water availability due to storm track shifts and increased temperatures. There is medium confidence among the five models that eastern China in DJF will experience drier conditions.

4.6.5 Potential impacts

The current population of China is over 1.3 billion with a population growth rate of 0.629% [CIA, 2008]. An increase in population will likely increase water and energy demands unless per
capita water and energy consumption decrease significantly. The construction of the Three Gorges Dam ensures a large renewable energy supply assuming it is operational. Population growth, rapid urbanization, and dependence on water intensive industry, as well as, reservoirs that don’t meet safety regulations are all high-risk characteristics in an area facing significant climate uncertainties. Fortunately, China is relatively independent of international water sources since they have only 2 international water treaties, both with Russia concerning borderline rivers [International Freshwater Treaties Database, 2008]. International conflicts may or may not become an issue but disputes among Chinese provinces or between urban and agricultural centers could arise if the regional climate changes significantly through the 21st century.

China also faces issues such as agricultural losses, reduction of glacial melt water, saltwater intrusion, sea level rise, animal and plant extinctions, and health concerns [IPCC WG2, 2007]. Lin et al. [2004] found that the yield of rain-fed rice could decrease by 5 to 12% in China due to a temperature increase of 2°C. As temperatures rise, glaciers are increasingly threatened. A quarter of a billion people in China depend on glacial melt for their water supplies [Stern, 2007]. The timing of glacial melt will shift but it will eventually decrease as the glaciers retreat further. Other water-related impacts of climate change in this region include the threat of saltwater intrusion into the groundwater in coastal regions where groundwater has been over-exploited [Han et al., 1999]. In addition, sea level rise could flood low-lying areas, impacting millions of people [Stern, 2007]. A 30 cm sea level rise would inundate 81,348 km² of coastal land in China [Du and Zhang, 2000]. The impact of climate change on ecosystems is also great in this region. 105 to 1,522 plant species and 5 to 77 vertebrates are projected to face extinction due to doubled CO₂ conditions [Malcolm et al., 2006]. Humans also face health risks. Hales et al. [2002]
projects that the risks of dengue fever will be greater and Takahashi et al. [2007] projects increased deaths from heat-related stress.

4.7 Eastern Siberia

4.7.1 Present Day Water Cycle Influences and Vulnerabilities

Due to its minimal development, the societal impacts of water availability changes in eastern Siberia (54.5N to 76.5N, 101E to 177E) would be small at a regional level. However, eastern Siberia has the ability to impact the globe through large methane emissions associated with permafrost melting. Permafrost is a major carbon reservoir; Siberia and Alaska are estimated to contain approximately 500 Gt of carbon in frozen yedoma (Pleistocene-age loess permafrost), approximately 400 Gt of carbon in non-yedoma permafrost, and between 50 and 70 Gt of carbon in western Siberian peatbogs [Zimov et al., 2006].

Northern Siberia lakes are also a larger source of atmospheric methane than previously thought. Between 1974 and 2000, the expansion of thaw lakes in northern Siberia has been linked to a 58% increase in lake methane emissions [Walter et al., 2006]. Fortunately, if Siberia gets wetter as well as warmer, the growth of natural vegetation would draw CO₂ from the atmosphere, helping to limit the growth in its contribution to greenhouse capacity.

4.7.2 Observed and modeled 20th century climate

Of the five AR4 GCMs used in this study, MIROC and GFDL come the closest to the observed CRU TS 2.0 dataset surface air temperatures in eastern Siberia (Figure 4.13). GISS is the only model that overestimates observed temperatures in the region. It is also the only model that does not match the small, observed warming trend. Figure 4.13 also shows 20th century modeled and observed precipitation. CCCma does the best job matching the observed values. There is a small trend toward
increasing values in observed precipitation that is similar to trends in the models. With the exception of CCCma, the GCMs tend to overestimate the precipitation in eastern Siberia in the 20th century. MIROC is the biggest outlier for precipitation with 10 mm/mo in excess of observations at many points during the 100-year period. SDDI calculated with observed temperature and precipitation shows an increasing trend in the 20th century that is not captured by the models. Unfortunately, there are no soil moisture measurements available near eastern Siberia from the International Soil Moisture Network [2010]. There is a mixture of increasing (GFDL, GISS and MIROC) and decreasing (CCCma and HadCM3) trends among the five models over eastern Siberia during the 20th century.

4.7.3 Projected changes in 21st century water availability

The mean changes projected by the IPCC models for the A1B scenario show increased rainfall, but on average small decreases in soil moisture, with much inter-model variability [IPCC, 2007].

4.7.3.1 Boreal Summer

Model projections for summertime in eastern Siberia at the end of the 21st century show big changes in the cryosphere. There is reduced snow amount, sea ice area and sea ice thickness compared to 20th century summers (Figures 2.17 and 4.14). Due to the reduced snow and ice cover, there is also decreased surface albedo, which acts a positive feedback by absorbing more incoming radiation and warming the surface.

The increased surface air temperatures (Figures 4.5, 2.12) increase the ability of the atmosphere to hold moisture. A monsoonal low-pressure system in central Asia transports moisture, which brings warm, moist air up the eastern coast of Asia in all models except for MIROC. Moisture is then advected in to Siberia and results in increased precipitation (Figure 4.5).
SDDI projections indicate wetter conditions (Figure 4.5). The increased precipitation wins out over small potential evapotranspiration values. The SDDI is limited by the Thornthwaite potential evapotranspiration, which is set to zero at temperatures below freezing. This is relevant for both JJA and DJF. Also, springtime runoff is not included in the SDDI formulation but it is in soil moisture. Thus precipitation changes largely influence the behavior of SDDI in this region. The soil moisture shows marginally drier conditions because the influence of temperature on soil moisture outweighs the precipitation increases.

4.7.3.2 Boreal Winter

Eastern Siberia model projections in the winter months at the end of the 21st century show increased precipitation (Figure 4.5) due to increased relative and specific humidity, increased upwelling from warming temperatures, and the ability of the atmosphere to hold more moisture in warmer temperatures. There is also a weakening of the Siberian High in all models. This leads to a weaker wind flow across the region.

SDDI projections are for wetter conditions. Increased precipitation wins out over small potential evapotranspiration values. Soil moisture shows mixed projections among models. The significant increase in precipitation seems to closely balance evapotranspiration.

4.7.4 Most likely scenarios

In JJA, eastern Siberia is likely to experience large changes in climate including increased temperatures due to albedo changes and increased precipitation due to an increase in atmospheric water content. The water availability impacts from increased temperature and precipitation tend to somewhat balance each other in this season. However, the soil moisture projections of slightly drier conditions are more plausible in part because of the limitations of the SDDI’s Thornthwaite potential evapotranspiration at low temperatures and partially because the GCMs tended to
overestimate 20\textsuperscript{th} century precipitation. There is medium confidence that eastern Siberia will become wetter during JJA over the 21\textsuperscript{st} century.

DJF conditions are likely to become wetter in eastern Siberia than in the 20\textsuperscript{th} century due to increased relative and specific humidity and upwelling. There is a very high confidence among the five models that conditions will be wetter in DJF over the next century. This is the only region where SDDI projections are wetter than soil moisture because of the limitations of Thornthwaite potential evapotranspiration at below freezing temperatures.

4.7.5 Potential impacts

High temperatures in eastern Siberia are dangerous because of the potential for enhanced methane release from permafrost and lakes. The increased CO\textsubscript{2} uptake by new vegetation growth in the region will most likely be overshadowed by significant methane increases, which would further exacerbate global warming trends. As temperatures rise, Siberia could also see a rapid increase in available water due to snow and glacier melting, which could lead to floods. Drifting ice can cause floods by blocking water channels, which leads to rising river water levels [Izrael \textit{et al.}, 2002]. Another threat to the region is that temperature increases combined with increased human activity in the region have been linked to a dramatic increase in fires in the Siberian peatlands. 20 million ha were burnt in 2003. Fires pose serious threats to both human health and air quality [Rachmanin \textit{et al.}, 2004]. Extreme summer temperatures and heat waves pose an additional threat to human health in the region [Zolotov and Caliberny, 2004].
4.8 Australia

4.8.1 Present Day Water Cycle Influences and Vulnerabilities

Australia (43.5S to 12.5S, 112E to 153.5E) is a climatically diverse country with a tropical climate in the north, a dry climate in the western and central regions, and a temperate climate on the eastern coast, which is home to a large percentage of the national population. There is a great deal of variation in annual rainfall between Australia’s regions. Drought is a yearly reality in many areas; the deserts in central and western Australia receive on average less than 250 mm per year of rainfall. In contrast, annual average precipitation in some tropical areas is sometimes in excess of 2,500 mm [AGNWC, 2008]. The high average precipitation in the north is in part due to the summer monsoon and tropical cyclones between December and April. The temperate regions receive rain in all seasons.

The Australian monsoon season occurs during the austral summer. The strength of the monsoon is variable from year to year, and is highly influenced by ENSO, MJO, and tropical cyclone activity [Kullgren and Kim, 2006; IPCC, 2007]. During warm phase ENSO years in June, July and August, eastern Australia typically experiences anomalously dry conditions and has become widely associated with drought. Although the drought in 2009 occurred during a La Niña, La Niñas will generally act to prolong the duration of the monsoon [Kim et al., 2006]. While the influence of MJO on the monsoon is small compared to the influence of ENSO, Kim et al. [2006] find that the MJO plays a major role in the onset and termination of the monsoon.

Cyclone activity is also associated with ENSO (Note: GCMs are currently unable to resolve cyclones). In Australia, above average tropical cyclone seasons are typical of La Niña years, while below average tropical cyclone activity is associated with El Niño [Plummer et al., 1999; Kuleshov and de Hoedt, 2003; IPCC, 2007]. The February 2011 category-5 cyclone that struck
northeastern Australia occurred during a La Niña event. It should be noted that GCMs are unable to resolve atmospheric phenomenon on such a small scale.

Australia’s TARWR are close to 492,000 GL [Water, 2006]. However, annual water use is only 24.06 GL, about 5% of the TARWR. Although Australia is the driest inhabited continent, it offers great potential for renewable water capture and storage. As of 2005, Australia had the ability to store 83,853 GL of water and was close to half capacity with 39,959 GL [CIA, 2008]. Australia is not vulnerable with respect to energy due to a decrease in water storage. Appropriately, with such a large variability in water resources, Australia is not heavily dependent on hydroelectric power. Currently, approximately 15,530 thousand MWh are generated annually, which represents only 6.6% of Australia’s total power production.

Domestic, industrial and agricultural freshwater withdrawals are approximately 15%, 10% and 75% respectively. The agricultural sector uses a large percentage of the freshwater supplies, due in large part to the fact that between 10% and 40% of cultivated land in Australia is currently irrigated. Although industrial water use only accounts for 10% of the fresh water withdrawals, four out of five of Australia’s top industries, mining, food processing, chemicals and steel, are considered intensive water use industries [Morikawa et al., 2007]. A decrease in water availability could impact major industries in addition to agriculture, which accounts for only 3% of Australia’s GDP.

In June 2004, the Australian government passed the National Water Initiative in an effort to address the need for sustainable water management. In response to the initiative, the National Water Commission was created to oversee progress towards water reform. They focused specifically on unlicensed activities with a significant impact on catchment yields. For example,
The Great Artesian Basin Sustainability Initiative received funding to repair boreholes, which were allowing water to flow uncontrolled from a precious nonrenewable groundwater resource.

### 4.8.2 Observed and modeled 20th century climate

Thus far, Australia has seen an average temperature increase of up to 0.25°C per decade between 1979 and 2005 [IPCC, 2007]. Between 1901 and 2005, Australia has experienced up to a 20% decrease per century in precipitation along the southwestern and northeastern coast and up to a 40% increase in central and northwestern areas [IPCC, 2007]. Major metropolitan regions around Sydney and Melbourne have experienced minor changes in precipitation. Precipitation in these regions ranges between a 5% decrease per century to a 20% increase [IPCC, 2007].

Of the five AR4 GCMs used in this study, HadCM3, MIROC and GFDL are all very close to the observed CRU TS 2.0 dataset surface air temperatures in Australia (Figure 4.15). GISS overestimates the temperature in this region by approximately 1.5°C for most of the 20th century. CCCma underestimates the temperature in the early part of the century but tracks the observations closely by the end. All models show the same warming trend as the observations. Figure 4.15 also shows 20th century modeled and observed precipitation. CCCma and HadCM3 do the best jobs matching the observed values. There is no clear trend in the modeled or observed precipitation. There is also no clear trend in the SDDI calculated with observed temperature and precipitation although there is a decreasing trend in SDDI for all the models in the 20th century, which seems to be related to the increased temperatures. In situ soil moisture measurements for Australia are available to a depth of 0.9 meters between 2003 and 2010 [ISMN, 2010]. The average 0.9-meter soil moisture measurement for 2003 to 2010 from 1 station on the southeastern coast of Australia is 317.07 kg/m² with a standard deviation of 7.40 kg/m². To compare with GCM soil moisture, the measurements would need to reach 3 to 4 meters in depth. However, a brute force scaling of this
0.9-meter average brings the soil moisture to a comparable range with the GCMs with the exception of GFDL (Figure 2.22). All models display negative soil moisture trends in the 20\textsuperscript{th} century except GFDL, which shows no trend.

### 4.8.3 Projected changes in 21\textsuperscript{st} century water availability

According to the IPCC AR4, Australia will experience warming similar to the global average [IPCC, 2007]. The Australian monsoon is projected to increase in intensity during the southern summer, likely due to the fact that the continental-scale land-sea thermal contrast will become larger [IPCC, 2007]. High-resolution models also project an increase in peak wind intensities and increased near-storm precipitation in future tropical cyclones [IPCC, 2007]. This would bring more precipitation in the summer. However, there is disagreement among models on the future magnitude of warming in the eastern tropical Pacific relative to the western tropical Pacific, which heavily influences the Australian monsoon and tropical cyclones in the region [IPCC, 2007]. The models are also unclear on the future characteristics of the Inter-decadal Pacific Oscillation, which has a weak negative correlation with the monsoon [IPCC, 2007], and the Indian Ocean Dipole, which is negatively correlated with rainfall over Australia [Ashok et al., 2003].

Looking at individual climate regions of Australia, the AR4 finds that precipitation is likely to decrease in southern Australia in winter and spring and in southwestern Australia in winter. This decrease in precipitation is at least partially due to the poleward expansion of the Hadley Cell over Australia. There is no agreement among models about precipitation changes in northern or central Australia [IPCC, 2007].
4.8.3.1 Austral Summer

By the end of the 21st century, model projections of Australia in DJF show large increases in surface air temperature and mixed changes in precipitation (Figure 4.5). SDDI and soil moisture projections agree that conditions will become drier in three models, GISS, CCCma and GFDL. HadCM3 and MIROC project severe drying in SDDI and very little change in soil moisture (Figure 4.5).

Southern Australia is likely to see more drying. All models show decreased precipitation in southern Australia (Figure 2.14). A study by Meneghini et al. [2006] found the phase of the Southern Annular Mode (SAM) inversely related to rainfall in southern Australia. Figure 4.16 shows the shift in SAM (SLP difference between 40°S and 65°S) in the last thirty years of the 21st century relative to the last thirty years of the 20th century during DJF. CCCma is the only model without stratospheric ozone and GISS is the only one of the remaining models with a non-recovering ozone hole. Ozone recovery is likely to lessen the SLP between mid and high southern latitudes and therefore the models without recovery should show more of a positive shift in SAM. We do see that GISS and CCCma have a substantial positive shift. The magnitude of tropical warming (tropical warming divided by southern hemisphere warming) is also relevant to shifts in SAM. A small magnitude of tropical warming should result in at most a small positive shift, or perhaps even a negative one, depending on the extratropical response. GFDL and MIROC both showed relatively large magnitudes of tropical warming (1.282 and 1.175 respectively compared to the smallest, CCCma with 0.925).

Northern Australia is likely to see less drying according to all models except HadCM3. The Australian monsoon is stronger in GISS, CCCma, and MIROC. An in-phase relationship between the SAM and rainfall is expected [Meneghini et al., 2006]. All models except GFDL
follow expectations with rainfall; GFDL has reduced precipitation in the north and a weaker Australian monsoon. Precipitation is influenced by general downwelling over land in all models except MIROC and is linked to intensification of the ITCZ.

There are discrepancies in soil moisture projections due to regional variations. In MIROC, southeastern Australia has increased soil moisture due to increased precipitation and weak evaporation. In HadCM3, southern Australia has increased soil moisture due to weak evaporation.

4.8.3.2 Austral Winter

The Australian winter at the end of the 21st century has strong temperature increases and decreases in precipitation in all models except CCCma (Figure 4.5). SDDI projects severe drying while soil moisture projections are mixed.

Southern Australia is projected to see more drying in Southwest. Decreased precipitation is expected in this region with a more positive SAM (Figure 4.17). Figure 4.17 shows the contributions to the positive shift in SAM we see in JJA: lack of ozone hole recovery, enhanced southward sensible heat transport at high latitudes, and a large magnitude of tropical warming. Ozone hole recovery, decreased southward sensible heat transport and a large tropical warming to southern hemisphere warming ratio all act to hinder the positive shift in SAM. The strengthened midlatitude jetstream is shifted south of Australia in all models except HadCM3. Models with the largest shift in SAM both show decreased precipitation in southern Australia as expected (GISS and GFDL). Northern Australia is projected to see decreased precipitation. CCCma is the only model with precipitation increases and has the largest “local” SAM increase.

During the 20th century, many JJA El Niño events were associated with decreased precipitation over Australia. Of the three models that display an El Niño-like base state change in
average tropical Pacific SSTs and decreased ENSO variability (CCCma, GFDL and MIROC),
two show a decrease in 21st century precipitation (GFDL and MIROC). Future decreased
precipitation over Australia may be associated with both mean state changes and changes in
ENSO variability in these three models.

There are discrepancies in soil moisture projections due to regional variations. Central
Australia in HadCM3 and southeastern Australia in MIROC have increased surface soil moisture
due to increased precipitation, weak evaporation and accumulation. In MIROC, southeastern
Australia has increased surface soil moisture due to increased precipitation and weak
evaporation. In HadCM3, central Australia has increased surface soil moisture due to increased
precipitation and weak evaporation.

4.8.4 Most likely scenarios
In DJF, southern Australia is likely to see drying due to a positive shift in SAM. Northern
Australia will likely see less drying due to a stronger monsoon dampening the impact of high
temperatures and evaporation. There is high confidence among the five models that Australia, on
average in DJF will become drier. In JJA, the austral winter, southern Australia is likely to see
more drying in the Southwest due to decreased precipitation and the mid latitude jet stream
shifting south of the region. Northern Australia is also likely to see decreased precipitation in JJA
and drier conditions. There is medium to high confidence that the average conditions in Australia
in JJA will be drier over the next century. Uncertainties in ENSO projections remain high.
Changes in ENSO patterns are likely to influence these results.

4.8.5 Potential impacts
The current population of Australia is approximately 21,450,000 with a population growth rate
of 0.824% [CIA, 2008]. An increase in population will likely increase water demand unless per
capita water consumption decreases. Although Australia is not dependent on water from other countries, there is potential for conflict within Australia if widespread drying does occur. Stakeholders include rural communities, urban communities, homeowners, industries, environmentalists, farmers, as well as individual municipalities. With a decreased freshwater supply, conflicts among stakeholders are likely.

Apparently Australians realize the importance of water given their efforts to preserve and store water, stay relatively independent of hydroelectric power generation and enact water sustainability initiatives [Bates et al., 2008; CIA, 2008]. This is a prudent stance given their above average vulnerability to water availability shifts. If conditions become drier, some of Australia’s top industries, mining, food processing, chemicals and steel, which are all considered intensive water-use industries, will be impacted [Morikawa et al., 2007]. In addition, the agricultural sector will require increased irrigation and face potential crop failure.

By the year 2080, as outlined by IPCC WG2 [2007], potential impacts to Australian ecosystems include catastrophic mortality of coral species annually, 95% decrease in distribution of Great Barrier Reef species, 65% loss of Great Barrier Reef species in the Cairns region, 46% of wet tropics endemic vertebrates lose core habitat, and reduced calcification for 70% of the area where deep sea corals occur [Jones, 2004; Jones et al., 2004; Crimp et al., 2004; Williams et al., 2003; Poloczanska et al., 2007].

4.9 The Middle East

The final focus region in this chapter is the Middle East (0 to 45N, 20E to 65E), which fully encompasses 17 countries: Djibouti, Egypt, Eritrea, Greece, Iran, Iraq, Israel, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Sudan, Syria, Turkey, United Arab Emirates, and Yemen. These boundaries also include portions of Pakistan, Afghanistan, Turkmenistan, Ethiopia, Somalia,
Libya, Chad, Central African Republic, South Sudan, Azerbaijan, Georgia, and Bulgaria. This section is a simple overview of future water availability projections for the Middle East. A full investigation into water availability vulnerabilities and potential impacts for this region will be the focus of a separate study.

4.9.1 Projected changes in 21st century water availability

All five models agree that surface air temperatures rise in the 21st century (Figure 4.18). Figure 4.18 shows modeled 36-month running average temperatures reaching between 23°C-26°C by the year 2100. SDDI values from all five models indicate conditions up to 6 standard deviations drier than the 1928 to 1978 reference period (Figure 4.18). However, there is disagreement among models on precipitation and soil moisture projections (Figure 4.18). MIROC is the only model to display increased precipitation and soil moisture in the 21st century. GFDL and GISS both show a discernible decrease in precipitation and soil moisture. The only indication of wetter conditions in the projections comes from the increased precipitation and soil moisture in MIROC. MIROC shows increased precipitation throughout the region during JJA and in northern Africa, southern Saudi Arabia, Yemen and Oman in DJF (Figure 2.14). Soil moisture increases follow the same regional pattern as precipitation increases in MIROC (Figure 2.22). All other model projections indicate either no change or a shift to drier conditions.

4.10 Conclusions

Over the next century, rising temperatures and changes in precipitation over land will influence water availability in regions across the globe. In this chapter, I have described our experience in using five different models and two measures of water availability to predict changes in water availability for seven regions.
There are only two regions out of the seven where there is a broad consensus between models and water availability measures for both summer and winter. The two regions are the southwestern U.S. and southern Europe and for both regions and both seasons, conditions will likely become considerably drier in the 21st century. In the southwestern U.S., in JJA there is a weakening of the North American Monsoon System and in DJF, storm tracks are shifted poleward despite an increase in the subtropical jet. In southern Europe, during JJA precipitation decreases due to ridging moving poleward over Eurasia while in DJF, the Northern Annular Mode becomes increasingly positive, shifting storm tracks northward and leaving reduced precipitation in southern Europe.

Two other regions show agreement between models and water availability measures, but only for a single season, Colombia in JJA and eastern Siberia in DJF. In Colombia, model projections show a weakening of the tropical circulation cell causing mild drying in western Colombia and slightly stronger drying in eastern Colombia. Current ENSO teleconnections may remain according to the three models that display an El Niño-like base state change in average tropical Pacific SSTs in the 21st century; they all show decreased precipitation. Eastern Siberia shows agreement between models and measures that conditions are likely to become wetter in the boreal winter in the 21st century due to increased upwelling and atmospheric water content.

In regions where there was disagreement between water availability measures, the 20th century observed and modeled temperature and precipitation was examined to see if the models uniformly overestimated or underestimated values to evaluate whether conditions would likely be slightly wetter or drier than estimated by GCM SDDI or soil moisture. This was the case for Uruguay in DJF, where we found that most models underestimate precipitation in the 20th century. Uruguay is likely to continue to be influenced in DJF by tropical teleconnections, which
are associated with increased precipitation during El Niño periods. CCCma had the closest match to the observed precipitation and GFDL was recognized as the model with the most skill simulating ENSO. The difference between the CCCma and GFDL SDDI and soil moisture projections were considered to be a range in likely regional water availability projections. This was also the case in eastern Siberia during JJA, where soil moisture showed slight drying and SDDI projected wetter conditions. Precipitation is thought to increase in the next century due to the advection of moist air into Siberia from a monsoonal low-pressure system in central Asia, which moves warm, moist air up the eastern coast of Asia. In this region models tended to overestimate precipitation in the 20th century, which makes the slightly drier conditions projected by the soil moisture more plausible.

In regions where models and water availability measures disagree, the most weight was placed on models that were able to best capture 20th century temperature and precipitation patterns in addition to displaying plausible changes in atmospheric dynamics. This is the most common situation for regional projections. For Uruguay in JJA, discrepancies between soil moisture projections between models were handled by avoiding the use of any projections that were heavily influenced by a small anomalous area within the region. Uruguay during JJA is likely to experience mild drying due to increased atmospheric stability and a southward shift in storm tracks. During DJF in Colombia there will likely be a strengthening of the tropical circulation cell. Western Colombia may see moderate or fluvial conditions and eastern Colombia will likely face continued drying. Projections of the severity of drying were moderated due to the underestimation of 20th century observed precipitation by the GCMs in Colombia.

Two regions, eastern China and Australia, show disagreement among models and water availability measures in both JJA and DJF. In eastern China in JJA, we expect continental
warming to pull the monsoonal rainfall northward causing northeastern China to become wetter and southeastern China to see very little change. In DJF, a positive shift in Northern Annular Mode is thought to shift storm tracks away from the region and cause mild water availability changes. In the southern hemisphere, the Southern Annular Mode is also likely to see a positive shift causing drying in southern Australia. Northern Australia will also likely see drying although dampened by a stronger monsoon. In JJA, there will likely be drying in southwestern and northern Australia due to decreased precipitation.

Disagreements between models and drought measures make it difficult to predict the future of water availability with great certainty. Nevertheless, we believe it is valuable to characterize water availability to the best degree to which our models and measures are capable. Doing so helps us understand the disagreements between predictions, which is an essential first step towards reconciling conflicts between models and measures. Modelers are currently preparing for the CMIP4 simulations; we look forward to learning whether it offers greater convergence in regional predictions and water availability measures.
5 Key Findings and Future Research

This thesis has demonstrated that although there is disagreement between water availability measures and among GCMs, both are useful tools for interpreting future climate change-induced shifts in fresh water availability over land. Key findings by chapter are below, followed by a summary of contributions to the field, limitations of existing models and measures, potential solutions for overcoming predictive shortfalls, and finally, proposed future research.

5.1 Key Findings

Chapter One

Chapter One introduced two water availability measures that are used throughout this thesis, soil moisture and the SDDI. We found that LSMs show steeper declining trends in soil moisture than GCMs for the years 1979 to 2010, which indicate that GCMs may be overestimating future soil moisture. GCMs are already projecting increases in drought severity and extent in the 21st century; Soil moisture changes indicate that the average percent of land gridboxes experiencing 5% drought conditions will increase from 3% to approximately 20% for all five GCMs (CCCma CGCM3.1 T47, GFDL CM2.1, GISS ER, HadCM3 and MIROC V3.2 medres) by the end of the century. SDDI projections are more extreme with 5% drought conditions reaching up to 45% of land gridboxes by the year 2100. According to SDDI, 21st century GCM projections show conditions rivaling North American historic mega-droughts.

The dependence of SDDI on $E_P$ calculations was also explored in Chapter One. It is not the $E_P$ methods with the smallest magnitudes but the $E_P$ methods that show the least sensitivity to temperature that produce the least severe SDDI and PDSI projections more similar to soil moisture.
Chapter Two

Chapter Two discussed the characteristics, biases and water availability projections of five IPCC AR4 GCMs (Table 1.1). The influence of the IPCC SRES A2 storyline versus the A1B storyline on SDDI is in most cases smaller than the differences between the GCMs for SDDI. All models show an increase in both dry and wet extreme conditions for SDDI and soil moisture. Increases in these extremes are more balanced for soil moisture projections than SDDI. HadCM3 soil moisture is the exception because wet extremes do not occur as much as dry extremes. All models exhibit the same behavior for SDDI; dry extremes outweigh wet extremes leading to large decreases in the global mean over the 21st century.

The agreement between models for the change in surface air temperature, precipitation, soil moisture and SDDI between the early and late 20th century is generally lower than the agreement between the late 20th century and late 21st century. Between the early and late 20th century, approximately 83% of land gridboxes have the same sign of temperature change while agreement is 100% for the 20th to 21st century difference. Soil moisture shows the least agreement between models on the sign of change. The agreement between soil moisture and SDDI changes is low, although it increases by over 100% in the 21st century. In only 1 out of every 8 gridboxes is there a unanimous indication of the sign of future water availability change.

Chapter Three

Chapter Three deconstructed soil moisture and SDDI in order to determine the ways in which they can be altered to become more like one another. Initial SDDI sensitivity tests showed that SDDI calculated with Hargreaves $E_p$ shows the most similarity to soil moisture. A multiple regression analysis found that SDDI is more sensitive to temperature than soil moisture.
Although we found that the Thornthwaite $E_p$, which is used to calculate SDDI is less sensitive to temperature than the aerodynamic $E_p$ used to determine soil moisture.

A key component to understanding the differences and similarities of soil moisture and SDDI is the $E_p$ scaling factor, $\beta$, which determines GISS evaporation. Evaporation is dampened and SDDI becomes more similar to soil moisture when $\beta$ is added to the SDDI formula. Increasing the surface conductance, a component of $\beta$ in the GISS GCM formulation, not only creates more realistic 20th century surface air temperature in the northern hemisphere all year long and precipitation during the summer in the northern hemisphere but also brings the SDDI and soil moisture closer to one another.

Chapter Three also showed that soil moisture and SDDI differences are related to their dependence on previous conditions. For most of the models in this study, due to the 0.897-factor in its formulation, SDDI is influenced for a longer period by events in the past. Synoptic variability in the winter is not strong enough to limit the water availability memory to six months. SDDI, PDSI and soil moisture are influenced for multiple years by previous events. Increasing surface conductance also increased soil moisture memory bringing soil moisture closer to SDDI.

The conclusion of Chapter Three was that since neither measure is perfect, multiple water availability measures should be used in tandem for their complementary strengths. When they disagree, the model characteristics, biases and ability to match observations in the region as well as the region’s temperature regime (Thornthwaite $E_p$ is not as reliable at low temperatures) should be considered. When the measures agree, a strong case can be made for the robustness of the future water availability projections.

*Chapter Four*
Chapter Four explored likely changes in regional water availability in seven regions: the southwestern U.S., southern Europe, Uruguay, Colombia, eastern China, eastern Siberia and Australia. In spite of the regional disagreements we observed between models and water availability measures in some of these areas, we outlined the most likely scenarios of changes to water availability in the 21st century based on model and water availability consensus, plausibility of thermodynamic and dynamic climatic shifts, and the ability of models to simulate regional observations. These future scenarios can be summarized as follows:

For both the southwestern U.S. and southern Europe, conditions will likely become considerably drier in the 21st century in JJA and DJF. In the southwestern U.S., in JJA there is a weakening of the North American Monsoon System and in DJF, storm tracks are shifted poleward despite an increase in the subtropical jet. In southern Europe, during JJA, precipitation decreases due to ridging moving poleward over Eurasia. In DJF, the Northern Annular Mode becomes increasingly positive, which is associated with a northward shift in storm tracks and is likely to cause reduced precipitation in southern Europe.

Uruguay is likely to continue to be influenced in DJF by tropical teleconnections, which are associated with increased precipitation during El Niño periods. CCCma had the closest match to the observed precipitation and GFDL was recognized as the model with the most skill simulating ENSO. The differences between the CCCma and GFDL SDDI and soil moisture projections provide a range of likely regional water availability projections. For Uruguay in JJA, we handled discrepancies between soil moisture projections between models by avoiding the use of any projections that were heavily influenced by a small anomalous area within the region, and concluded that Uruguay during JJA is likely to experience mild drying due to increased atmospheric stability and a southward shift in storm tracks.
In Colombia, JJA model projections show a weakening of the tropical circulation cell, causing mild drying in western Colombia and slightly stronger drying in eastern Colombia. Current ENSO teleconnections may remain according to the three models that display an El Niño-like base state change in average tropical Pacific SSTs in the 21\textsuperscript{st} century; they all show decreased precipitation. During DJF in Colombia there will likely be a strengthening of the tropical circulation cell. Western Colombia may see moderate or fluvial conditions and eastern Colombia will likely face continued drying. Projections of the severity of drying were moderated due to the underestimation of 20\textsuperscript{th} century observed precipitation by the GCMs in Colombia.

In eastern China in JJA, we expect continental warming to pull the monsoonal rainfall northward causing northeastern China to become wetter and southeastern China to see very little change. In DJF, a positive shift in Northern Annular Mode associated with a northward shift in storm tracks is likely to cause mild water availability decreases.

Eastern Siberia shows agreement between models and measures that conditions are likely to become wetter in the boreal winter in the 21\textsuperscript{st} century due to increased upwelling and atmospheric water content. In the boreal summer, precipitation in eastern Siberia will probably increase in the next century due to the advection of moist air into Siberia from a monsoonal low-pressure system in central Asia, which moves warm, moist air up the eastern coast of Asia. In this region models tended to overestimate precipitation in the 20\textsuperscript{th} century, which makes the slightly drier conditions projected by the soil moisture more plausible.

In DJF, the Southern Annular Mode is likely to see a positive shift causing drying in southern Australia. Northern Australia will also likely see drying although dampened by a stronger monsoon. In JJA, drying is likely in southwestern Australia due to a poleward shift in the mid latitude jet stream associated with a positive shift in SAM.
5.2 Summary of Contributions

In order to better predict water availability in the next century, this work seeks to reconcile discrepancies between models and water availability measures and to better understand the different regional impacts of climate change on water availability. To that end, this dissertation provides the following new contributions to the field:

- An analysis of the global and zonal differences between soil moisture and SDDI (Chapter One and Two)
- Identification of the regions where soil moisture and SDDI agree and disagree (Chapters Two and Four)
- An explanation for differing projections in soil moisture and SDDI (Chapters One, Two, Three and Four)
- The ability to bring convergence to soil moisture and SDDI future projections, which is also applicable to the widely-used PDSI (Chapter Three)
- An examination of the seasonal and long-term memory of soil moisture, SDDI and PDSI (Chapter Three)
- An analysis of the most likely scenarios for 21st century hydrologic responses to climate change in seven regions: southwestern U.S., southern Europe, Uruguay, Colombia, eastern China, eastern Siberia and Australia (Chapter Four)
- A detailed presentation of the differences and similarities of five GCMs (Chapters One, Two, Three, Four)

5.3 Limitations of Existing Models and Measures

It is impossible for models to ever do a perfect job in simulating climate because of mankind’s limited understanding of the vast complexity and subtlety of feedbacks in the climate system.
Even for those mechanisms that are fully understood, we are still currently limited by computing power and time. Regardless of inherent limitations, models continue to improve year after year. Models are often able to produce many realistic current climate features and some of the models in this study are able to reasonably capture complex atmospheric oscillations and teleconnections. With that stated, there is always room for improvement since we are still far from being limited in the modeling world by a lack of climate system knowledge.

Although high resolution GCMs will not solve all problems and will inevitably introduce new challenges and computing times, regional features with small-scale spatial variability such as soil moisture, vegetation types and precipitation would likely benefit from higher resolution coast lines and orography. In addition, improving the simulation of ENSO, NAM, SAM as well as other modes of variability are critical to for creating a realistic climatology.

However, there are also many issues that can be improved regardless of resolution. In Chapter Three, we explored the problem in the GISS model that surface (i.e. canopy) conductance values are always much smaller than atmospheric conductance leading to the vegetation always limiting evapotranspiration. By increasing surface conductance we were able to better match 20th century observations of surface air temperature in the northern hemisphere all year long and precipitation during the summer in the northern hemisphere. The GISS model evaporation’s dependence on aerodynamic potential evapotranspiration, surface conductance and atmospheric conductance is at the root of this problem. Aerodynamic potential evapotranspiration is an order of magnitude larger than pan evaporation measurements and other potential evapotranspiration methods. Currently, the surface conductance has to be unrealistically small in order to compensate for the overestimated potential evapotranspiration and maintain realistic evaporation values. This is likely to become a bigger issue as global warming alters surface and atmospheric conductance
values. Another important innovation in climate models is the implementation of dynamic vegetation, which will hopefully be included in the next generation of GCMs.

Climate models and their ability to simulate soil moisture have a fair number of limitations, but as we have seen, so do drought indices. As temperatures increase, we face a new climate regime in which techniques for measuring drought that focused on precipitation deficits (e.g. the Standardized Precipitation Index) are insufficient for capturing the influence of climate change on the hydrologic cycle, such as the influence of increased temperature and incoming shortwave radiation on evapotranspiration or changes in snowmelt on runoff. Unlike PDSI, SDDI is blind to runoff, recharge, vegetation and soil type. However, a formula based on the difference between the atmospheric supply and demand is powerful in its simplicity particularly during a period of climate change. Perhaps the influence of climate change should be examined more closely for additional drought indices.

5.4 Potential Solutions for Overcoming Predictive Shortfalls

Five practical ways to minimize and overcome many of the predictive shortfalls of models and measures of water availability are to:

1) Continue implementation of GCM improvements as discussed in the previous section,

2) Use multiple water availability measures with an understanding of their strengths and limitations,

3) Add root-zone soil moisture with one specified depth as a required variable to CMIP simulations,

4) Support efforts to strengthen the global coverage of in situ soil moisture measurements in the International Soil Moisture Network, and
5) Use hydrologic satellite data, such as global root-zone soil moisture measurements (SMAP mission scheduled to launch in 2013) for model calibration.

Some suggestions can be immediately implemented such as using multiple measures. The addition of a well defined, root zone soil moisture to CMIP variables may be difficult to deliver given the differences between models but would be very helpful for inter-model comparison, particularly once dynamic vegetation schemes are implemented. There is currently a total soil moisture and surface soil moisture value (upper 0.1m of soil column) for most CMIP3 models. The other suggestions are long-term ongoing processes such as GCM development, calibration and expanding global in situ measurement networks. My proposed future research was inspired by the prospect of utilizing available global high-resolution hydrologic data.

5.5 Proposed Future Research

An increasing amount of satellite remote sensing-based hydrologic data has recently become available for comparison with climate models, including the first long-term (24-year) evapotranspiration (ET) dataset [Zhang et al., 2010]. In light of the opportunity this data provides, I would like to: (1) to conduct a full comparison of modeled and observation-derived ET; and (2) to analyze to the full surface water balance and partitioning of ET and runoff, which would attempt to answer the following questions:

- Is the observed surface water cycle balanced? How about the modeled surface water cycle?
- Are GCMs over- or underestimating ET? What about drought indices?
- Is the seasonal cycle in the Zhang ET dataset captured in the ET from GCMs?
- Are there particular geographical regions of discrepancy between the modeled and observed ET? If so, why?
• How well do GCMs and LSMs capture ET and runoff partitioning in the water cycle?

These questions focus on the land surface and the global hydrologic cycle, but ET also affects the global energy balance. Changes in ET impact the most basic climatic variables, temperature and precipitation, so answers to these research questions are valuable not only to researchers in drought monitoring and modeling, but also to the broader climate modeling community.

5.6 Final Thoughts

A global decrease in freshwater over land is a legitimate threat of human-induced climate change. Although regions will be influenced in different ways, global shifts in water resources will influence people across the world. Changes in water availability could have devastating societal, environmental and economic impacts on health, agriculture, energy production, and transportation to name only a few areas. We have an opportunity to implement changes now in regions and sectors with the highest risks. For example, this thesis has identified two regions, the southwestern U.S. and southern Europe, which show agreement between soil moisture and SDDI in five GCMs that future water availability will decrease. Although there is considerable uncertainty in 100-year predictions, findings with such widespread agreement between measures and models should not simply be ignored, however strong the impulse is to discount future threats. Mitigating the potential impacts of climate-induced water availability change should be a top priority today for stakeholders with long-term interests, which includes industry, city and state planners, policy makers, decision makers and of course, mankind.
<table>
<thead>
<tr>
<th>Land-Surface Scheme Description</th>
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<tbody>
<tr>
<td><strong>Canadian Centre for Climate Modeling and Analysis (CCCma)</strong></td>
<td><strong>NOAA Geophysical Fluid Dynamics Laboratory (GFDL)</strong></td>
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<tr>
<td>CCCma uses the CLASS land-surface scheme, which includes 3 soil layers, a snow layer where applicable, and a vegetative canopy treatment [Verseghy et al., 1993].</td>
<td>MIROC uses the MARSRO land-surface scheme [Takahashi et al., 2000].</td>
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<td><strong>NOAA Geophysical Fluid Dynamics Laboratory (GFDL)</strong></td>
<td><strong>Hadley Centre for Climate Prediction (HadCM3)</strong></td>
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<td>GFDL uses a land-surface scheme with 1 canopy layer, 5 soil layers ranging from 0 cm to 200 cm in thickness, and a surface runoff scheme that depends on the amount of snow. TOPMODEL is used for surface runoff, which is based on the amount of snow.</td>
<td>HadCM3 uses the MOSES land-surface scheme [Cox et al., 1999].</td>
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<tr>
<td><strong>Goddard Institute for Space Studies (GISS)</strong></td>
<td><strong>University of Tokyo Center for Climate System Research Medium-Resolution Model (MIROC)</strong></td>
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<tr>
<td>GISS uses a land-surface model with 1 canopy layer, 0-3 snow layers depending on the amount of snow, and 6 soil layers with thicknesses of 0.1, 0.25, 0.65, and 2.0 meters.</td>
<td>MIROC uses the MARSRO land-surface scheme [Takahashi et al., 2000].</td>
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<tr>
<td><strong>Hadley Centre for Climate Prediction (HadCM3)</strong></td>
<td><strong>University of Tokyo Center for Climate System Research Model 3.2 Medium-Resolution (MIROC)</strong></td>
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<td>HadCM3 uses the MOSES land-surface scheme [Cox et al., 1999].</td>
<td>MIROC uses the MARSRO land-surface scheme [Takahashi et al., 2000].</td>
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<td>MIROC uses the MARSRO land-surface scheme [Takahashi et al., 2000].</td>
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<td>GLDAS Models</td>
<td>Soil Layers</td>
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<td>Community Land Model (CLM 2.0)</td>
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Table 1.3: Satellites with soil moisture retrieving ability

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<tr>
<th>Satellite</th>
<th>Resolution</th>
<th>Operations</th>
<th>Agency</th>
<th>Sensor</th>
<th>Time</th>
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<tr>
<td>SMOS</td>
<td>30-50 km</td>
<td>ESA</td>
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<td>AQUA</td>
<td>50 km</td>
<td>NASA</td>
<td>Multi-frequency radiometer with LAWA</td>
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<td>METOP</td>
<td>25/50 km</td>
<td>ESA</td>
<td>C-Band Scatterometer (ASCAT)</td>
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<td>ERS-1 and ERS-2</td>
<td>25/50 km (active) 40 km (passive)</td>
<td>ESA</td>
<td>Cooperation with EUMETSAT</td>
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Table 1.4: JJA mean 1961-1990 potential evapotranspiration (mm/day) using local weather data inputs from Rochester, NY (left column) and GISS GCM inputs from the gridbox covering the region (right column).

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<thead>
<tr>
<th>Method</th>
<th>Local Data</th>
<th>GISS GCM</th>
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<tr>
<td>ASCE Penman-Monteith (full)</td>
<td>4.75</td>
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<td>ASCE Penman-Monteith Standardized Form</td>
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<td>FAO 56 Penman-Monteith</td>
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<td>FAO Plan Protection Paper 17 Penman</td>
<td>6.07</td>
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<td>FAO 24 Corrected Penman</td>
<td>5.27</td>
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<td>FAO 24 Penman</td>
<td>5.27</td>
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<td>Hargreaves (1985)</td>
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<td>Priestley-Taylor (1972)</td>
<td>5.5</td>
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<td>1948/1963 Penman</td>
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<td>1982,96 Kimberly Penman</td>
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Table 2.1: Overview of GCMs. Information is adapted from the IPCC AR4 WG1 Tables 8.1 and 8.2 [IPCC, 2007]. In addition, stratospheric ozone and volcanic forcing is adapted from Miller et al. [2006] and deep convection is adapted from Lin et al.

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<tr>
<th>Model ID, Vintage</th>
<th>Sponsor(s), Country</th>
<th>Atmosphere</th>
<th>Top Resolution</th>
<th>References</th>
<th>Sea Ice Dynamics, Leads</th>
<th>Transient Climate Response (°C)</th>
<th>Climate Sensitivity (°C)</th>
<th>Volcanic Forcing</th>
<th>Geochemical Cycles and Fossils, Ammonia, Fungi</th>
<th>Land, Soil, Plants, Routing</th>
<th>Sea Ice, Ocean, Atmosphere</th>
<th>Ocean, Atmosphere, Land, Soil, Plants, Routing</th>
<th>Land, Soil, Plants, Routing</th>
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Table 2.2: GCM forcing agents adapted from IPCC AR4 WG1 Table 10.1 [IPCC, 2007]. Entries mean Y: forcing agent is included; C: forcing agent varies with time during the 20th Century Climate in Coupled Models (20CM) simulations and is set to constant or annually cyclic distribution for scenario integrations; and n.a.: forcing agent is not specified in either simulations and scenario integrations.

| Model                      | CO₂ | CH₄ | N₂O | Stratospheric | Tropospheric | CFCs | SO₂ | Urban Black carbon | Organic carbon | Nitrate | Fire aerosols | Sea salt | Dust | Sea | VOC | Black carbon | CO | CH₄ | N₂O | CH₂O | CH₃Cl | Chlorophyll a | Phycocyanin | PSII Efficiency | N₂O | NH₃ | Sea Salt | Land Use | Other | Sea | Total Vertical | CFCs | SO₂ | Urban Black carbon | Organic carbon | Nitrate | Fire aerosols | Sea salt | Dust | Sea | Sea Salt |
|----------------------------|-----|-----|-----|--------------|--------------|------|-----|-------------------|----------------|---------|---------------|---------|------|-----|-----|----------------|----|-----|-----|------|-------|-----------------|-------------|----------------|-------|-----|---------|----------|-----|-----|---------------|----------------|---------|---------------|---------|------|-----|---------|
| CCCMA                      | Y   | Y   | Y   | C            | Y            | Y    |     | Y                 | Y              | Y       | Y             | Y       | Y    | Y   | Y   | Y              | Y  | Y   | Y   | Y    | Y     | Y              | Y           | Y              | Y     | Y   | Y       | Y        | Y   | X   | Y              | Y              | Y       | Y             | Y       | Y    | Y    | Y       |
| CGCM3.1                    | Y   | Y   | Y   | C            | C            | Y    |     | Y                 | Y              | Y       | Y             | C       | Y    | Y   | Y   | C              | Y  | Y   | Y   | Y    | Y     | C              | Y           | Y              | Y     | Y   | Y       | Y        | Y   | X   | Y              | Y              | Y       | Y             | Y       | Y    | Y    | Y       |
| GFDL-CM2.1                 | Y   | Y   | Y   | Y            | Y            | Y    |     | Y                 | Y              | Y       | Y             | Y       | Y    | Y   | Y   | Y              | Y  | Y   | Y   | Y    | Y     | Y              | Y           | Y              | Y     | Y   | Y       | Y        | Y   | X   | Y              | Y              | Y       | Y             | Y       | Y    | Y    | Y       |
| GISS-ERI                   | Y   | Y   | Y   | Y            | Y            | Y    |     | Y                 | Y              | Y       | Y             | Y       | Y    | Y   | Y   | Y              | Y  | Y   | Y   | Y    | Y     | Y              | Y           | Y              | Y     | Y   | Y       | Y        | Y   | X   | Y              | Y              | Y       | Y             | Y       | Y    | Y    | Y       |
| MIROC3.2(M)                | Y   | Y   | Y   | Y            | Y            | Y    |     | Y                 | Y              | Y       | Y             | Y       | Y    | Y   | Y   | Y              | Y  | Y   | Y   | Y    | Y     | Y              | Y           | Y              | Y     | Y   | Y       | Y        | Y   | X   | Y              | Y              | Y       | Y             | Y       | Y    | Y    | Y       |
| UKMO-HadCM3                | Y   | Y   | Y   | Y            | Y            | Y    |     | Y                 | Y              | Y       | Y             | Y       | Y    | Y   | Y   | Y              | Y  | Y   | Y   | Y    | Y     | Y              | Y           | Y              | Y     | Y   | Y       | Y        | Y   | X   | Y              | Y              | Y       | Y             | Y       | Y    | Y    | Y       |
Table 2.3: Palmer Drought Severity Index (PDSI) classifications, which can also be applied to SDDI

<table>
<thead>
<tr>
<th>Palmer Classifications</th>
<th>PDSI Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely dry</td>
<td>-4.0 or less</td>
</tr>
<tr>
<td>Severe drought</td>
<td>-3.0 to -3.99</td>
</tr>
<tr>
<td>Moderate drought</td>
<td>-2.0 to -2.99</td>
</tr>
<tr>
<td>Mild drought</td>
<td>-1.0 to -1.99</td>
</tr>
<tr>
<td>Incipient dry spell</td>
<td>-0.5 to -0.99</td>
</tr>
<tr>
<td>Near normal</td>
<td>-0.49 to 0</td>
</tr>
<tr>
<td>Incipient wet spell</td>
<td>0.0 to 0.49</td>
</tr>
<tr>
<td>Slightly wet</td>
<td>0.5 to 1.99</td>
</tr>
<tr>
<td>Moderately wet</td>
<td>2.0 to 2.99</td>
</tr>
<tr>
<td>Very wet</td>
<td>3.0 to 3.99</td>
</tr>
<tr>
<td>Extremely wet</td>
<td>4.0 or more</td>
</tr>
</tbody>
</table>
Table 2.4: This table shows the percentage of gridboxes in which all five GCMs agree on the sign of change in surface air temperature (T), precipitation (P), soil moisture (SM) and SDDI over land (and combinations of these variables) for two intervals: 1) (1981 to 2000)AVE- (1901 to 1920)AVE and 2) (2081 to 2100)AVE- (1981 to 2000)AVE. The third column shows the percentage of gridboxes in which the multi-model average agrees with the sign of change in the observations [Mitchell and Jones, 2005]. n.a. indicates values that are not available.

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>P</td>
<td>16.26%</td>
<td>47.83%</td>
<td>61.25%</td>
</tr>
<tr>
<td>T</td>
<td>82.79%</td>
<td>100.00%</td>
<td>98.52%</td>
</tr>
<tr>
<td>SM</td>
<td>9.76%</td>
<td>13.96%</td>
<td>n.a.</td>
</tr>
<tr>
<td>SDDI</td>
<td>38.89%</td>
<td>56.91%</td>
<td>61.34%</td>
</tr>
<tr>
<td>P and T</td>
<td>6.64%</td>
<td>36.72%</td>
<td>38.23%</td>
</tr>
<tr>
<td>P and - T</td>
<td>7.18%</td>
<td>11.11%</td>
<td>22.33%</td>
</tr>
<tr>
<td>P and SM</td>
<td>3.66%</td>
<td>7.45%</td>
<td>n.a.</td>
</tr>
<tr>
<td>P and - SM</td>
<td>0.27%</td>
<td>1.08%</td>
<td>n.a.</td>
</tr>
<tr>
<td>P and SDDI</td>
<td>10.57%</td>
<td>16.67%</td>
<td>35.71%</td>
</tr>
<tr>
<td>P and - SDDI</td>
<td>0.14%</td>
<td>2.03%</td>
<td>6.95%</td>
</tr>
<tr>
<td>SM and SDDI</td>
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<td>5.69%</td>
<td>13.90%</td>
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<tr>
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<td>51.22%</td>
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<tr>
<td>SM and - SM</td>
<td>2.98%</td>
<td>1.76%</td>
<td>n.a.</td>
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<tr>
<td>SM and - SDDI</td>
<td>5.83%</td>
<td>12.20%</td>
<td>n.a.</td>
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<tr>
<td>SDDI and - SM</td>
<td>4.74%</td>
<td>11.38%</td>
<td>n.a.</td>
</tr>
<tr>
<td>SDDI and - SDDI</td>
<td>0.27%</td>
<td>0.27%</td>
<td>n.a.</td>
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*For Multi-Model Average and Observations
<table>
<thead>
<tr>
<th>Region</th>
<th>Soil Moisture Regression</th>
<th>Annual SDDI Regression</th>
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<tr>
<td><strong>Southwestern United States</strong></td>
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<td>$T_{soil}$</td>
<td>$T_{soil}$</td>
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<tr>
<td>cccma</td>
<td>0.43</td>
<td>0.74</td>
</tr>
<tr>
<td>gfdl</td>
<td>0.47</td>
<td>1.21</td>
</tr>
<tr>
<td>giss</td>
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<tr>
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<td>0.84</td>
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<tr>
<td>miroc</td>
<td>8.39</td>
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Table 3.1 Multiple linear regression
Table 3.2: Number of gridboxes that agree on original SDDI and soil moisture conditions

<table>
<thead>
<tr>
<th>Soil Moisture (%)</th>
<th>80% - 100%</th>
<th>70% - 80%</th>
<th>60% - 70%</th>
<th>50% - 60%</th>
<th>40% - 50%</th>
<th>30% - 40%</th>
<th>20% - 30%</th>
<th>10% - 20%</th>
<th>0% - 10%</th>
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<tbody>
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<td>5</td>
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% of time 2071-2199 is wetter than 1928-1978
Table 3.3: Number of gridboxes that agree on SDDI with fixed $\beta$ and soil moisture conditions

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<th>Fixed Beta SDDI</th>
<th>SOIL MOISTURE</th>
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<th>60 to 40</th>
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% of Time 2071-2199 is warmer than 1928-1978. % of Time 2071-2100 is warmer than 1928-1978.
<table>
<thead>
<tr>
<th>Dynamic Beta SDDI</th>
<th>SOIL MOISTURE</th>
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Table 3.5: Temperature and precipitation RMS differences between the model and observations from the 1XSC and 3XSC GISS GCM runs

### Temperature: RMS Differences

#### 3XCC - 1XCC (January)

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<tbody>
<tr>
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<td>Ocean</td>
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<td>Ground</td>
<td>-0.740</td>
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<td>-1.409</td>
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#### 3XCC - 1XCC (July)

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#### 3XCC - 1XCC (Annual)

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<td>Ground</td>
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### Precipitation: RMS Differences

#### 3XCC - 1XCC (January)

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#### 3XCC - 1XCC (July)

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#### 3XCC - 1XCC (Annual)

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Table 4.1: Pressure changes (Pa) in 21st century NAM

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<td>427.18</td>
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<td>427.18</td>
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<td>-245.44</td>
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<tr>
<td>Mid Lats - High Lats</td>
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<td>84.16</td>
<td>-185.43</td>
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<td>-185.43</td>
<td>270.11</td>
<td>84.16</td>
<td>-185.43</td>
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21st Century Pressure Shift in Modeled NAM
Figure 1.1: 1979-2010 global monthly soil moisture from GLDAS Land-Surface Models
Figure 1.2: 1901-2100 global monthly soil moisture projections from 3 AR4 GCMs using Climate of the 20th Century and the SRES A2 scenario for the 21st Century.
Figure 1.3: Global monthly GCM soil moisture (% change from 1979-1989 average) with a 12-month running average.
Figure 1.4: Global monthly LSM soil moisture (% change from 1979-1989 average)
Figure 1.5: Percent of gridboxes in North America experiencing 5% drought conditions or worse in June, July, and August from 1BC to 2100AD with respect to the 1928-1978 reference period. The 1901-2100 GCM SDDI values are annual. All of the time series are smoothed with a 3-year running average. The grey lines represent the 100-year running standard deviation of the Cook PDSI for the first 2006 years and the largest GCM standard deviation (from MIROC).
Figure 1.6: Percent of gridboxes in North America experience 5% drought conditions in June, July and August from 1870 to 2100 with respect to the 1928-1978 reference period.
Figure 1.7: Global average of the percent of gridboxes in 5% drought or worse in JJA over land only using SDDI and soil moisture with 1928-1978 reference period.
Figure 1.8: Variety of potential evapotranspiration values for Rochester, NY calculated with local weather station data.

Each timeseries is smoothed with a 12-month running average.
Figure 1.9: Variety of potential evapotranspiration values for New York from the GISS Climate of the 20th Century IPCC run. Each timeseries is smoothed with a 12-month running average.
Figure 1.10: Annual percentage change in 2080-2089 EP methods relative to 1970-1999 conditions (left). Annual (2080 to 2089) AV E – (1970 to 1999) AV E SDDI (upper right) and PDSI (lower right) for Rochester, NY calculated using multiple EP methods for the MIROC, GFDL and GISS GCMs. [Courtesy of Richard Goldberg]
Figure 1.11: Global average potential evapotranspiration over land from 1901 to 2100 with the GISS GCM
Figure 1.12: Global average SDDI calculated with 4 different potential evapotranspiration methods from 1901 to 2100. Note: After the first 2.5 years of the 2046-2065 and 2081-2100 periods, all 3 of the Hargreaves methods are essentially the same. In the Hargreaves 1 method, SDDI resets to zero after each break in data. In the Hargreaves 2 method, SDDI resumes with the last available SDDI value. In the Hargreaves 3 method, a linear trend is calculated using the 24-month average at the beginning and end of the previous period to estimate the value of SDDI at the beginning of the next period. After the first 2.5 years of the 2046-2065 and 2081-2100 periods, all 3 of the Hargreaves methods are essentially the same.
Figure 2.1: 20th century zonal observed and modeled surface air temperature annual anomalies from the 1928-1978 average.
Figure 2.2: Land-only surface air temperature (°C; upper left) and land-only and global precipitation (mm/mo; upper and lower right) anomalies from 1971-2000 averages and Global cloud cover (%; lower left) over land shown as anomalies from the 1971-2000 averages divided by the 1971-2000 standard deviation for 5 GCMs and temperature and precipitation observations.
Figure 2.3: 20th century zonal modeled and observed precipitation annual anomalies from 1928-1978 averages (mm/mo)
Figure 2.4: Annual soil moisture and SDDI. SDDI is calculated using modeled and observed surface air temperature and precipitation and soil moisture anomalies from the 1971-2000 averages divided by the 1971-2000 standard deviation. These are projections from five GCMs for 1901-2100. Negative SDDI indicates drier conditions.
Figure 2.5: Zonal observed and modeled surface air temperature annual anomalies from the 1928-1978 average
Figure 2.6: JJA and DJF zonal average land-only surface air temperature (K) and precipitation (mm/mo) differences between (2071-2100) and (1971-2000)\textsuperscript{2}. Negative latitudes are in the southern hemisphere.
Figure 2.7: Zonal modeled and observed precipitation annual anomalies from 1928-1978 averages (mm/mo)
Figure 2.8: JJA and DJF zonal land-only SDDI and soil moisture (% change) differences between (2081-2100) and (1981-2000). Negative values are in the southern hemisphere.
Figure 2.9: Zonal modeled land-only SDDI (left column) and soil moisture (right column, kg/m²) annual anomalies from 1928-1978 averages.
Figure 2.10: JJA and DJF 1901-2100 zonal 200mb to 800mb mean dp/dt anomalies (Pa/min) from the 1928-1978 mean. Note that positive values indicate a relative increase in downwelling.
Figure 2.11: This series of maps shows the time series correlation between SDDI and surface air temperature on the top row, the correlation between soil moisture and surface air temperature on the second row, the correlation between SDDI and precipitation on the third row, and the correlation between soil moisture and precipitation on the bottom row for all models.
Figure 2.12: JJA and DJF GCM surface air temperature (K) for 1971-2000 (top two rows) and the (2071-2100)AV-E-(1971-2000)AV-E surface air temperature change (K) on the bottom two rows.
Figure 2.13: 1971-2000 observed mean JJA and DJF surface air temperature (°C) and precipitation (kg/m^2)
Figure 2.14: JJA and DJF GCM precipitation (mm/mo) for 1971-2000 (top two rows) and the (2071-2100) AV - (1971-2000) AV precipitation change (mm/mo) on the bottom two rows.
Figure 2.15: JJA and DJF GCM vertical velocity ($\frac{dp}{dt}$ in Pa/min) for 1971-2000 (top two rows) and the JJA and DJF (2071-2100) AV E vertical velocity (Pa/min) on the bottom two rows. Positive $\frac{dp}{dt}$ indicates downwelling.

<table>
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<tr>
<th>Model</th>
<th>CCCma</th>
<th>HadCM3</th>
<th>GFDL</th>
<th>MIROC</th>
<th>GISS</th>
</tr>
</thead>
</table>
Figure 2.16: Monthly anomalies of mean snow cover extent between November 1966 and January 2011 mean.

The anomaly of a given interval anomalies are calculated from the November 1966 to January 2011 mean.
The bottom graph (c) shows the period 1901-2100 with observations and GCM projections. Running monthly means are plotted on

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Figure 2.17: GCM mean snow amount (kg/m²) over land during December, January and February for 1971-2000 and 2071-2100.
Figure 2.18: These figures show the percentage of gridboxes in each model experiencing 5% drought or 5% flood conditions in JJA (upper left) and DJF (upper right) as well as 5% flood (or wetter) conditions in JJA (bottom left) and DJF (bottom right) as measured by soil moisture.
Figure 2.19: These figures show the percentage of gridboxes in each model experiencing 5% drought (or drier) and 5% flood (or wetter) conditions in JJA (upper left) and DJF (upper right), as well as 5% flood (or wetter) conditions in JJA (bottom left) and DJF (bottom right) as determined from SDDI.
Figure 2.20: SDDI trends between 1901 and 2100 using modeled surface air temperature and precipitation from five models for two IPCC SRES scenarios: A2 and A1B.
Figure 2.21: 1979-2010 mean soil moisture (kg/m²) from four LSMs.
Figure 2.22: JJA and DJF GCM soil moisture (kg/m²) for 1979-2010 (top two rows) and (2071-2100)AV-E-(1971-2000)AV-E soil moisture change (kg/m²) on the bottom two rows. Note: the colorbar scales for GFDL and MIROC are different from CCCma, GISS and HadCM3.
Figure 2.23: 1971-2000 JJA and DJF SDDI calculated with observed surface air temperature and precipitation.
Figure 2.24: JJA and DJF GCM SDDI for 1971-2000 and 2071-2100.
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Figure 3.3: SDDI with potential evapotranspiration scaled by 1.2 minus SDDI with unaltered potential evapotranspiration.

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We wetter Drier
Figure 3.4: Potential evapotranspiration (Ep) vs. surface air temperature using aerodynamic method (upper left) and Thornthwaite method (upper right). GISS GCM Evaporation vs. surface air temperature is on the bottom left. The bottom right graph shows unlimited Thornthwaite Ep vs. surface air temperature. Note: The upper left figure has a different vertical scale than the others. Aerodynamic Ep is an order of magnitude greater than Thornthwaite Ep and evaporation. Orange dots represent 1971-2000 averages and green dots represent 2071-2100 averages.
Figure 3.5: Percentage occurrence of drought/flood in 2071-2100 relative to 1928-1978 using soil moisture (far right) and SDDI.
Figure 3.6: Evaporation changes (mm/mo) are calculated from the GISS model using these simple approximations for the 21st century and the last 30 years of the 20th century. Changes are between the last thirty years of the 21st century and the last 30 years of the 20th century.

GCM Soil Moisture:
\[
\Delta E = \beta \Delta EP + (\Delta \beta)EP
\]

PDSI:
\[
\Delta E = \beta \Delta EP
\]

SDDI:
\[
\Delta E = \beta \Delta EP + (\Delta \beta)EP
\]

Images on the top row and the bottom left. The bottom right image is the actual change in the GISS GCM evaporation (note: the scale is different).
Figure 3.7: Percentage occurrence of drought/flood in 2071-2100 relative to 1971-2000.

<table>
<thead>
<tr>
<th>Original SDDI</th>
<th>Soil Moisture</th>
<th>SDDI with fixed $\beta$</th>
<th>SDDI with dynamic $\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Driest</td>
<td>Wettest</td>
<td>Driest</td>
<td>Wettest</td>
</tr>
</tbody>
</table>

Legend:
- 0 to 20: Light yellow
- 20 to 40: Orange
- 40 to 60: Red
- 60 to 80: Dark red
- 80 to 100: Dark blue

Figure: Percentage occurrence of drought/flood in 2071-2100 relative to 1971-2000.
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Figure 3.8: 1901-2100 timeline of global mean land-only original SDDI, SDDI with fixed $\beta$, SDDI with dynamic $\beta$ and soil moisture in standard deviations away from the 1928-1978 average.
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