21st century drought outlook for major climate divisions of Texas based on CMIP5 multimodel ensemble: Implications for water resource management

Abstract

Management of water resources in Texas (United States) is a challenging endeavor due to rapid population growth in the recent past coupled with significant spatiotemporal variations in climate. While climate conditions impact the availability of water, over-usage and lack of efficient management further complicate the dynamics of supply availability. In this paper, we provide the first look at the impact of climate change projections from an ensemble of Coupled Model Intercomparison Project Phase 5 (CMIP5) on 21st century drought characteristics under three future emission trajectories: Representative Concentration Pathway (RCP) 2.6, RCP 4.5 and RCP 8.5, using the standardized precipitation index (SPI) and standardized precipitation evapotranspiration index (SPEI). In addition, we evaluate the performance of the ensemble in simulating historical (1950-1999) observations from multiple climate divisions in Texas.

Overall, the ensemble performs better in simulating historical temperature than precipitation. In semi-arid locations such as El Paso and Laredo, decreasing precipitation trends are projected even under the influence of climate policies represented by the RCP 4.5. There is little variability in the SPI across climate divisions and across RCPs. The SPEI, on the other hand, generally shows a decreasing trend towards the latter half of the 21st century, with multi-year droughts becoming the norm under the RCP 8.5, particularly in regions that are already dry, such as El Paso. Less severe droughts are projected for the sub-humid eastern edge of the state. Considering that state water planning agencies are already forecasting increased water shortages over the next 50 years, we recommend proactive approaches to risk management such as adjusting the planning tools for potential recurrence of multi-year droughts in regions that are already water-stressed.

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1 Introduction

Droughts are a normal part of climate and occur in virtually all parts of the world. However, in recent years droughts have been experienced with greater frequency and severity globally (Nielsen-Gammon, 2008; Mishra and Singh, 2010; Texas Water Development Board [TWDB], 2012; Dai 2013; Yu et al., 2014; Warren and Holman, 2014). Since the beginning of the 21st century, two major droughts in Texas, in 2006 and 2011, have already resulted in the loss of hundreds of lives, billions of dollars of agricultural losses via crop failure and thousands of square miles of land lost to wildfires (Combs, 2012; AghaKouchak and Nakhijiri 2012). The 2011 drought was the worst 1-year drought in recorded history for much of Texas. By October 2011, nearly 90% of the state was classified in the exceptional drought category (Combs, 2012); conditions did not improve for much of the state until 2013. Water planners in the state are tracking the inflows for the recent years and concluding that some regions, such as Wichita Falls and West Texas are in the middle of a new and more severe critical drought or experiencing a drought very similar to the critical drought of the 1950s.

The effects of long-term droughts, such as the 1950s drought and the late 1990s drought are more widespread, as they impact the quantity of water available from surface and groundwater resources, impair water quality and riparian habitats, and negatively impact energy infrastructure (Riebsame et al., 1994; Wilhite and Svoboda, 2000; Wilhite and Knutson, 2008). As such, the frequency of drought is expected to increase worldwide because of increasing temperatures and rainfall events tending to be shorter but more intense (Alexander et al., 2006; Shili et al., 2014; Wuebbles et al., 2014). For instance, South-eastern Australia was subject to extreme dry conditions in the form of millennial drought (1997-2009), followed by the wettest recorded two-year period in 2010-2011 (CSIRO, 2012). Several studies (Norwine and John, 2007; Nielsen-Gammon, 2008; Banner et al., 2010; Liu et al., 2011; Jiang and Yang, 2012; Hernandez and Uddameri, 2014; Wuebbles et al., 2014) based on climate models have projected rising temperatures for Texas in the 21st century, albeit with no significant trends in precipitation,

58 suggesting higher likelihood of droughts. Parts of the Southwestern United States, including Western
59 Texas have already been identified as being climate change ‘hotspots’ or areas highly vulnerable to the
60 impacts of climate change by Diffenbaugh et al. (2008).

61 On the demand side, the Texas Water Development Board (TWDB, 2012) projects that the water
62 demand in Texas will rise by 22% by 2060, from about 18 million acre-feet per year to about 22 million
63 acre-feet per year, creating more challenges for water supply planners. By 2060, urban areas are
64 expected to have the largest increases in water demand due to increased municipal water consumption
65 from rapid population growth. In particular, counties with major metropolitan areas, such as Harris
66 County (Houston), Bexar County (San Antonio), Dallas, Tarrant, Denton and Collin Counties (Dallas-Fort
67 Worth area) and Travis County (Austin) are anticipated to have the largest water deficits (difference
68 between projected supplies and demands). During the same period, groundwater supplies are expected
69 to diminish by ~ 30%, primarily due to decreased water availability from the Ogallala, over-usage, and
70 pumping restrictions to curb land subsidence in the Gulf Coast aquifer (TWDB, 2012). Surface water
71 supplies are projected to decline due to persistent dry conditions and decrease in inflows. Mace and
72 Wade (2008) suggest that future changes in climate resulting in more frequent droughts may induce a
73 greater reliance on groundwater, if surface water resources become less reliable.

74 Understanding the spatial and temporal characteristics of drought is thus critical for long-term water use
75 planning, particularly in a water-stressed state such as Texas. Although different classifications of
76 drought exist based on the hydroclimatic or socio-economic variable used to measure it, droughts
77 generally result from lack of precipitation for a sustained period of time. Evapotranspiration (ET) may
78 also play a significant role in drought by producing moisture deficits. Several drought indices, such as the
79 Palmer Drought Severity Index (PDSI; Palmer, 1965), Standardized Runoff Index (SRI; Shukla and Wood,
80 2008) and the Standardized Precipitation Index (SPI; McKee et al., 1993) have been applied to detect

and monitor drought. The SPI has been widely-used in drought assessment studies (e.g., Turkes and That, 2009; Ibrahim et al., 2010) but only accounts for precipitation. Over the last few years new indices such as the Joint Deficit Index (JDI; Kao and Govindaraju, 2010) and the Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Sorrano et al., 2010) have been introduced to overcome some of the shortcomings of the SPI. The JDI is a probability-based index that has been developed using copulas and can be used to assess the combined effects of multiple hydrologic variables such as precipitation and streamflow. Its ability to capture emerging and prolonged droughts has been demonstrated (Kao and Govindaraju, 2010; Mirabbasi et al., 2013). The SPEI includes evapotranspiration (ET), the loss element of the water balance, while retaining the positive features of the SPI. By including ET, the SPEI accounts for the impact of trends in another important climatic variable, temperature. Although the SPEI is a recent development in drought assessment, it has already been recommended as an alternative to the SPI to evaluate climatic water imbalances by several authors (e.g. Potop and Mozny, 2011; Begueria et al., 2013; Stagge et al., 2014).

Recently, Hernandez and Uddameri (2014) applied the SPEI to two Coupled Model Intercomparison Project Phase 3 (CMIP3) global climate models (GCMs) under two scenarios (Special Report on Emission Scenarios (SRES) A1B and B1) across different locations in South Texas and projected long periods of drought, ranging from 5 to 8 years, in the second half of the 21st century. However, their projections of intensification of future drought is based the Thornthwaite method of estimating PET, a method that has been suspected of overestimating drying with increasing temperatures (Lockwood, 1999). As part of the Southern Climate Impacts Planning Program (SCIPP), Liu et al. (2012) applied a set of 16 CMIP3 GCMs to assess the effect of future climate change on the Southern United States. Of the six states included in the study, Texas was found to have the greatest decrease in annual precipitation in the 21st century; additionally, drier regions were projected to get drier. Jiang and Yang (2012) simulated future changes in hydroclimatic variables across Texas using a suite of CMIP3 GCMs. Under the A1B scenario,

much of the state was projected to get drier towards the end of the 21st century. However, the authors point out that regional difference in climate factors such as moisture sources and topography across Texas strongly impact future patterns in temperature and precipitation and must be taken into account in drought assessment studies. The general conclusion from these studies is a drier regime towards the end of the 21st century. However, these projections are based on the SRES scenarios where the impacts of future regulations on emissions to have not been explored.

In response to the need for more sophisticated models and scenarios that capture the effect of policies, simulations from the new generation of GCMs have recently become available within the CMIP Phase 5 (CMIP5; Taylor et al. 2012). The CMIP5 models have higher spatial resolutions and are more comprehensive and as such provide new avenues for modeling the effects of climate change employing a wide range of alternative scenarios, known as Representative Concentration Pathways (RCPs) to aid in risk-based natural resource management. The simulation of climate from a single GCM is not sufficient to provide a thorough assessment of future hydrologic impacts or to adequately capture the uncertainties involved therein; the use of multi-model ensemble means has been shown to provide more vigorous projections of future changes and presents the most conservative approach from a risk-management perspective (Murphy et al., 2004; Raisanen, 2007; Tebaldi and Knutti, 2007; Sperna Weiland et al., 2012). The primary objective of this paper is, therefore, to provide the first look at the impact of climate change projections from an ensemble of CMIP5 GCMs on drought characteristics until the end of the 21st century under different mitigation scenarios in 10 cities, chosen as representative examples of the major climate divisions of Texas, using the SPI and SPEI. The novel feature of this study is that we have evaluated the performance of the ensemble in simulating historical observations at the chosen study locations and make recommendations on their suitability of application in the state.

2 Methodology

2.1 Study Area Characteristics

Owing to its sheer size and a number of local geographical influences, the climate of Texas is spatially diverse. There are ten distinct climatic regions as shown in Figure 1a (GIS shapefile sourced from NCDC, 2015), each with their own seasonal weather patterns (Nielsen-Gammon, 2008). 10 major urban areas, namely (1) Abilene, (2) Dallas-Fort Worth, (3) El Paso, (4) Houston, (5) Laredo, (6) Longview, (7) Lubbock, (8) McAllen, (9) San Angelo, and (10) San Antonio were chosen as illustrative examples of the 10 major climatic divisions in Texas. Other major urban areas, such as Amarillo, Austin, Corpus Christi, Midland, Waco and Wichita Falls were initially included in the study but trends in these locations were similar to the other chosen locations in their respective climate divisions and were hence left out to avoid redundancy. Despite the distinct features of each climate division, certain trends can be observed across the state. As shown in Figure 1b, annual mean precipitation decreases from the east (~ 1,500 mm/yr), which benefits from increased moisture supply from the Gulf of Mexico, to the west (~ 150 mm/yr). Annual mean temperature decreases from the south to the north (National Climate Data Centre [NCDC], 2014). Spatial variation in annual average maximum and annual average minimum temperatures are shown in Figure 1 (c) and (d), respectively. Most of the precipitation in the state occurs in the form of flash events that produce large amounts of rainfall in a short duration. The climate is also marked by extremes in temperature and precipitation, resulting in frequent droughts and floods. Intense rainfall associated with hurricanes is characteristic of the Gulf Coast of Texas while droughts occur throughout the state.

Availability of water has become a topic of significant importance in Texas because of the stresses imposed by climate conditions, over-usage driven by agriculture, significant population growth, and over-reliance driven by water use practices. In terms of the water supply usage in Texas, conjunctive

water use is common practice across the state. Lack of availability of traditional sources of supply (surface water and groundwater) is prompting various entities across the state to evaluate and adopt alternative sources of supply such as conservation, aquifer storage and recovery (ASR), brackish groundwater desalination, and direct and indirect reuse. Groundwater from the Edwards aquifer used to be the principal source of water for San Antonio; conservation efforts and recent projects such as Canyon Lake and desalination of brackish groundwater from the Carrizo Wilcox aquifer are addressing the need for alternative water sources to reduce the reliance on the Edwards aquifer (City of San Antonio, 2014). In the High Plains, groundwater, primarily from the Ogallala, is blended with surface water from various reservoirs. Recent dry conditions have prompted several direct and indirect wastewater reuse projects in the West Texas, most recently by the cities of Big Spring and Wichita Falls. Prolonged drought in the Rio Grande coupled with over-withdrawal has increased stresses on the Hueco- and Mesilla- Bolson aquifers shared with Mexico. To manage the lack of supplies from this source, El Paso has also been investigating the use of alternative water sources, such as aquifer storage and recovery (ASR), reclaimed wastewater, and brackish groundwater desalination (City of El Paso, 2014). El Paso is the most water-scarce location in this study, and the city has implemented significant water conservation strategies since the beginning of the new century. South Texas is characterized by semiarid climate, as a result of which less than 2% of this area is covered by perennial water bodies (TWDB, 2012). Yet, urban areas in this region are largely reliant on the Rio Grande and the Nueces River. Dallas, Abilene and San Angelo currently use surface water sources (TWDB, 2012) as the primary source of supply. Land subsidence issues along the coast of Texas have prompted regulations and restrictions on groundwater pumping thereby increasing the coastal region's reliance on surface water resources; surface water is also the source of water supply for Longview considering the abundance of this resource in East Texas.

2.2 Data Compilation

In order to provide consistent evaluation across analyses and to adequately capture inter-model variability, a suite of 22 CMIP5 models (see Table (i) for model names and sources) with hydroclimatic outputs available for the chosen RCPs and locations was selected for the study. The suite of GCMs represents the products of a diverse set of modeling groups and types [coupled atmospheric-ocean models (AOGCM), Earth System Models (ESMs) and models with atmospheric chemistry (ChemAO and ChemESM)]. Selection of GCMs was also based on the recommendations published in the TWDB study for the most appropriate GCMs for the state of Texas (Tummuri et al., 2013). This study also recommended using a GCM ensemble for analyzing the impact of climate change on hydrologic parameters. The RCP 2.6, 4.5, and 8.5 were chosen as they represent the lower, intermediate, and upper range of radiative forcings at the turn of the century, respectively, and allow for an investigation of the effect of future mitigation scenarios on moisture deficits.

Bias corrected and spatially disaggregated (BCSD) CMIP5 monthly temperature (average, minimum and maximum surface air) and monthly precipitation projections (1/8 degree) were compiled for the chosen 22 CMIP5 GCMs for the time period 1950-2099 under the RCP 2.6, 4.5 and 8.5 scenarios. This dataset was downloaded for each location based on a 1/8 degree grid cell corresponding to its latitude and longitude bounds. This resulted in a total of 10 grid cells with 1/8 degree resolution, one per location, each with coverage of roughly 160 km². This dataset is available online from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections archive at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/. It must be noted that the RCPs represent alternate future (21st century) scenarios and differences between them arise beginning only in the year 2005. For the sake of brevity, the time period 1950-1999 is henceforth referred to as the *historical* period; 2000-2049 is referred to as the *early* period, and the years 2050-2099 is referred to as the *late* period. In addition to GCM climate projections, 1/8 degree observed temperature and precipitation data for 1950-1999 (source: Maurer et al., 2002) was also compiled from the aforementioned archive for all 10 study

locations to aid in the evaluation of GCM performance for that period. Several methods and metrics are available and have been used to assess model performance in simulating historical observations and in hydroclimatic model validation (Watterson, 1996; Legates and McCabe Jr., 1999; Taylor, 2001; von Storch and Zwiers, 2003; Mudelsee, 2010; Cadule et al., 2010). These include the Root Mean Squared Error (RMSE), correlation coefficients, normalized model to data deviation measure, trend analysis, etc. Bayesian methods of addressing model inadequacies have been used as well but these are more complex in nature (Sexton et al., 2012). In essence, all these techniques attempt to represent the magnitude of a model's error or the simulated variability and as such, no individual technique can be considered superior. It has been pointed out (Tebaldi and Knutti, 2007; Knutti et al., 2013) that the joint use of many metrics of evaluation provides a better picture of model performance and hence we have used two straightforward and complementary measures of comparing simulated quantities with corresponding observations, the Mean Absolute Error (MAE), and the normalized standard deviation (NSD). Considering the inherent variability in precipitation, both the MAE and NSD tests were conducted at annual scales. Additionally, annual trends in the GCM and observed datasets were evaluated and compared using the modified Mann Kendall test.

The MAE is simply a statistical comparison of model predictions (P_i ; $i=1,2,\dots,n$) with corresponding observations (O_i ; $i=1,2,\dots,n$), the difference between the two being the model-prediction error. It is calculated as shown in Equation 1, where n is the total number of samples. MAEs are not measured on a scale - lower MAEs are simply suggestive of smaller model average errors.

$$MAE = \frac{\sum_{i=1}^n |P_i - E_i|}{n} \quad (1)$$

The normalized standard deviation is the ratio of model to observed standard deviations. It is calculated as shown in Equation 2 below:

$$NSD = \frac{SD_{model}}{SD_{obs}} = \frac{\sqrt{\frac{\sum_{i=1}^n (m_i - \bar{m})^2}{n}}}{\sqrt{\frac{\sum_{i=1}^n (o_i - \bar{o})^2}{n}}} \quad (2)$$

Where, SD represents standard deviation, 'm' represents the model simulated variable and 'o' represents the observed variable. The NSD provides a measure of the ability of the model to capture the observed variability; a value of NSD = 1 means that the observed variability is perfectly captured by the model, while values lower than or greater than 1 mean the variability is underestimated or overestimated by the model, respectively. Considering that GCMs were not developed to reproduce time series of observations, the modified Mann-Kendall (Hamed and Rao, 1998) test provides a means to assess their ability to capture long-term trends while also accounting for temporal autocorrelation. A significance level of 0.05 was adopted to evaluate trends. The fume package (Bedia, 2012) available through R statistical software (R Development Core Team, 2013) was used for the modified Mann-Kendall test.

2.3 Drought Index Calculation

The SPI is a probability-based drought index developed by McKee et al. (1993) that is widely used in drought monitoring. Recently, it was adopted as the standard meteorological drought index by the World Meteorological Organization (Sheffield and Wood, 2011; Hayes et al., 2011). The SPI is essentially a cumulative probability distribution of a long-term precipitation time series transformed into a normal distribution with a mean of zero and standard deviation of one. The SPI can be computed at various time-scales such as 1-month, 3-month, 12-month, etc. Being a standardized measure, it can be used to compare rainfall characteristics across locations, regardless of their respective climate features. Conceptually, the SPI represents the deviation of precipitation for a given location at a given time from

'normal conditions'. However, the SPI only accounts for one climate variable, precipitation, and does not consider losses through evapotranspiration. To calculate the SPI, a time-series of precipitation accumulated over a certain time period (1-month, 3-months, etc.) is first averaged over that time period and then fit to a probability distribution function. The two-parameter gamma distribution (Equation 3) and the Pearson III distribution have been widely used for fitting precipitation datasets (Guttman, 1999; Shukla et al.2010; Hernandez and Uddameri, 2014). Following Thom (1966), maximum likelihood solutions are typically used to estimate the α and β (shape and scale parameters, respectively) for the time scale of interest and each month of the year at each location, as given by Equations 4 to 6.

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \quad (3)$$

$$\alpha = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right) \quad (4)$$

$$\beta = \frac{\bar{x}}{\alpha} \quad (5)$$

$$A = \ln \left(\frac{\bar{x}}{x} \right) - \frac{\sum \ln \left(\frac{\bar{x}}{x} \right)}{n} \quad (6)$$

Where:

α , β are the shape and scale parameters, respectively

x is the amount of precipitation

$\Gamma(\alpha)$ is the gamma function

256 $\bar{x}$ is the mean precipitation

257 n is the number of observations

258 The optimal values of α and β are then used to find the cumulative probability of a precipitation event
259 for the given month and time scale of interest for that location. The probabilities from the fitted
260 cumulative density functions are then converted into the standard normal distribution. The resulting
261 normal distribution is the SPI and has a zero mean and a standard deviation (SD) of one. SPI values
262 between -1 and +1 indicate near normal or average moisture conditions as ~ 68% of data fall within this
263 range. SPI values greater than one represent wetter than average conditions while those less than -1
264 represent drier than average conditions. As the main focus of this study is drought assessment for future
265 water planning, all drought indices were calculated for a 12-month time scale as this reflects long-term
266 trends in moisture deficit and the consequent impact on related hydrologic variables such as streamflow
267 on an annual scale.

268 The SPEI, developed by Vicente-Serrano et al. (2012) is an evaluation of the deviation of moisture deficit,
269 calculated as the difference between precipitation and potential evapotranspiration (PET), in a given
270 time interval from 'normal conditions'. Its probability-based nature also makes it well-suited to this
271 study where risk management is critical. Moreover, the ability of the SPEI to reproduce drought
272 characteristics has been documented in many studies, e.g., Vicente-Serrano et al. (2012), McEvoy et al.,
273 (2012) and Wang and Chen (2014). The SPEI is also known to be equally sensitive to changes in
274 precipitation and PET (Vicente-Serrano et al., 2014). The SPEI is calculated in a manner analogous to the
275 SPI except that moisture deficits, not precipitation alone, are aggregated over a period of interest.
276 Considering that the difference between precipitation and PET can be positive or negative, a three-
277 parameter distribution is required to fit the probability distribution. Vicente-Serrano et al. (2010)
278 recommend log-logistic distributions as they generally fit extreme values better and hence we have

279 adopted this approach. The probability distribution function of the moisture deficit 'd' given by a log-
280 logistic distribution is shown in Equation 7 below:

$$281 \quad F(d) = \left\{ 1 + \left(\frac{\alpha}{d - \gamma} \right)^\beta \right\}^{-1} \quad (7)$$

282 In Equation 7, d represents the difference between precipitation and PET and α , β and γ represent the
283 shape, scale and location parameters which are estimated from the sample d. Calculating moisture
284 deficit or surplus requires an estimate of the PET, which can be achieved using temperature based
285 methods such as the Thornthwaite (Thornthwaite, 1948) and the Hargreaves (Hargreaves and Samani,
286 1982) or using more comprehensive methods (accounting for aerodynamic factors) such as the Penman-
287 Monteith ([PM], Monteith, 1981). It must be noted that the Hargreaves method includes a term for
288 extra-terrestrial radiation, which is calculated using the latitude and time of the year. Despite the
289 inclusion of this radiation term, the Hg method is commonly referred to as a temperature-only method.
290 These methods have been developed for different climatic conditions and require different input
291 variables (or combinations thereof) such as air temperature, net radiation, vapor pressure, and wind
292 speed. The PM method is generally considered to be the most robust method but is data intensive.
293 Where data availability is limited, the Thornthwaite method and the Hargreaves method have been
294 frequently used (Van der Schrier et al., 2011; Hernandez and Uddameri, 2014) as they require only
295 temperature data. The applicability of the Th method to climate assessment studies has been
296 questioned as the method tends to overestimate PET with increasing temperatures (Lockwood, 1999;
297 Donohue et al. 2010) and thus overestimate drying in a warming climate; we have corroborated these
298 findings by testing the method for our study locations (presented as supplementary material). Begueria
299 et al. (2013) recommend the use of the Hargreaves method over the Thornthwaite when data needed
300 for the PM method is insufficient or not available; hence, we have used the Hargreaves method to

compute PET, and subsequently SPEI, in this study. The SPI package (Neves, 2012) available through the R statistical software was used to compute the SPI while the SPEI package (Begueria and Vicente-Serrano, 2013) was used to compute the SPEI. The PET calculations were also performed within the SPEI package; the input variables for these calculations are simply the monthly maximum ($T_{\max}$) and monthly minimum temperatures ($T_{\min}$) and the latitude of that location. The latitude of the location is used to estimate mean external radiation (R_a) shown in Equation 8. Based on the SPI and SPEI, drought severity was classified as ‘near-normal conditions’, ‘moderately-dry’, ‘severely-dry’ and ‘extremely-dry’, as shown in Table (ii). For a given level of drought severity, additional metrics such as (a) the maximum continuous period of time when the drought index is below that level, (b) the duration (number of months) of the drought and (c) the evolution of these metrics from the historical to the early to the late time periods were calculated.

$$PET = 0.023R_a \left(\frac{T_{\max} + T_{\min}}{2} + 17.78 \right) \sqrt{(T_{\max} - T_{\min})} \quad (8)$$

3 Results

3.1 Evaluation of GCM performance in simulating historical observations

In the following discussions, the ensemble mean refers to the un-weighted average of the multi-model ensemble; the ensemble range refers to the spread (minimum-maximum) across the 22 GCMs. A comparison of the GCM-projected and observed annual mean temperature and annual total precipitation for the historical period for Dallas-Fort Worth, shown as a representative example, is presented in Figure 2 (parts a and b). It can be seen that the ensemble range largely captures the variability in observed temperature and precipitation for this period. However, the precipitation deficits that characterized the 1950s drought (Woodhouse and Overpeck, 1998) are not well-captured by the ensemble, as shown in Figure 2b. The observed climate variables largely fall within the ensemble range

at all other locations as well (presented as supplementary material). It can also be seen from Figure 2 that the SPI and SPEI, both derived from precipitation and/or temperature, for the observed dataset also largely fall within the ensemble range. However, the magnitude of the inter-annual variability in observations is larger than that of the ensemble mean due to the buffering nature of averaging across multiple models.

Projections of annual average temperature and annual total precipitation for the historical period of each of the 22 selected GCMs were compared with the observations using the MAE and NSD and the results from Dallas-Fort Worth are presented in Table (iii). The top five models ranked by smallest MAEs or by NSD equal to or nearly equal to 1 are highlighted in Table (iii). Unsurprisingly, the ensemble mean has the lowest (best) MAE. On the other hand, the ensemble mean has the worst NSD as it buffers the variability across the models. A comparison of the NSD across the GCMs indicates that virtually all models tend to underestimate the observed variability in precipitation and slightly overestimate the observed temperature variability. Using MAE as the model performance measure, the CCSM4.1 (expansion of model abbreviations, sources, type and resolution are provided in Table (i)) is the only model to rank in the top five for both temperature and precipitation simulations. Using NSD as the model performance metric, both the FIO-ESM.1 and GFDL-CM3.1 models rank in the top five models for both temperature and precipitation. It is also evident from Table (iii) that the HadGEM2-AO.1 and MIROC-ESM-CHEM.1 models rank highly for temperature simulations regardless of the metric (MAE or NSD) used. As such, the CCSM4.1 was the only model to consistently feature in the top five models at other locations in terms of the MAE and NSD (data not shown). The HadGEM2-AO.1, the CCSM4.1, the MIROC-ESM-CHEM.1 appear to have the best ability to capture the variability in the observed temperature at all chosen locations while the IPSL-CM5-MR.1 and GFDL-CM3.1 consistently featured in highly ranked models at other locations for capturing the variability in precipitation. No spatially consistent patterns were detected in model performance using the MAE. As such, El Paso and Laredo

were the only locations where most (at least 20 out of the 22 models) models underestimate the temperature variability.

Annual trends in temperature and precipitation for the observed and GCM dataset were evaluated using the modified Mann Kendall test at all locations for all models and for the ensemble mean. For the sake of brevity, only the results from Dallas-Fort Worth are shown in Table (iv). Statistically significant increasing trend detected in the observed precipitation data was reproduced by both the ensemble mean and the MIROC-ESM.1 model. No significant trends were detected in temperature but as can be seen from Table (iv), some models such as the FIO-ESM.1 and IPSL-CM5A-LR.1 falsely show increasing trends. Only the ensemble mean was able to consistently, on a spatial basis, capture observed trends; the results of this comparison are shown in Table (v) (precipitation) and Table (vi) (temperature). It can be seen from Table (v) that statistically significant increasing trends in precipitation for the historical observations have been duplicated by the ensemble mean at Dallas-Fort Worth, McAllen and San Antonio; the ensemble mean is unable to capture the increasing trends detected in historical observations at El Paso and Houston. On the other hand, the ensemble mean is able to reproduce increasing temperature trends at all locations where they were detected, such as Laredo, McAllen, San Angelo and San Antonio, as shown in Table (vi). On an individual basis, the CCSM4.1, the GFDL-ESM2M.1, the GISS-E2-r.1, the HadGEM2-AO.1 and the MIROC-ESM.1 were able to duplicate all observed statistically significant temperature trends (data not shown). As for precipitation, only the IPSL-CM5A-MR.1 model was able to reproduce the observed wetting trend at San Antonio. At El Paso, Houston and McAllen where significant wetting has been observed in the historical period, none of the models, on their own, were able to reproduce this trend (data not shown). Additionally, several models produce false positives, i.e., significant trends where none were observed, especially where precipitation is the variable of interest, as shown in Table (v).

GCM-projected trends in the ensemble mean at other time periods were also evaluated. For the early time period, no significant trends in precipitation are projected under the RCP 2.6 (Table (v)). Under the RCP 4.5, Houston is projected to experience an increase in precipitation while a decreasing trend is projected for McAllen and Laredo. At Laredo, a decreasing trend is projected under the RCP 8.5 as well. In the late period, many locations are projected to experience increasing precipitation under the RCP 2.6 as shown in Table (v). As for temperature, increasing trends are projected at all locations for both the early 21st century under all three RCPs. However, the RCP 2.6 does produce decreasing temperature trends at all locations during the late period while the RCP 4.5 and RCP 8.5 continue to produce warming trends at all locations. The data from the temperature trend analysis is not shown due to the spatial uniformity, i.e., significant warming or cooling at all locations.

Trends in the ensemble mean for the overall time period (1950-2099) were also evaluated using the modified Mann Kendall test. All three RCPs forecast statistically significant ($p < 0.05$) increasing temperatures at all locations and these results are thus not shown. It can be seen from Table (v) that the RCP 2.6 projects increasing annual precipitation at several locations, likely due to a rebound of precipitation in the latter half of the 21st century at these locations, as discussed earlier. On the other hand, both the RCP 4.5 and RCP 8.5 consistently project decreasing precipitation trends in the semi-arid locations such as Laredo, Lubbock and McAllen and also at San Antonio. Even sub-humid locations like Houston are projected to experience a decrease in precipitation under the RCP 8.5, likely due to decreasing trends in the late period.

3.2 Evaluation of the PET estimation method

In addition to evaluating GCM simulation of historical temperature and precipitation, it is imperative to assess the suitability of the Hargreaves method in simulating historical PET, as PET combined with precipitation jointly characterize the SPEI. The robustness of the PET derived from the GCMs is impacted

by the choice of PET estimation method, the Hargreaves (a temperature-based method), and consequently the capacity of the GCMs to simulate temperature, which was discussed earlier. As part of the Texas ET network, the Texas A&M AgriLife Extension (2013) computes monthly and annual total PET at various weather stations across the state. They use the PM method using the requisite weather parameters recorded over the last 50-60 years at these stations (Laredo, Longview and McAllen are not part of the Texas ET network and are thus omitted from this section). This data was compiled for comparison with the PET computed using the Hargreaves method applied to the CMIP5-model simulated temperature data for the 1950-1999 period. Considering that PET cannot be measured directly, we use PET computed from observed weather data using the PM method, which is generally considered to be the most suitable formulation, to ascertain the reliability of PET computed from the Hargreaves method for the same time period. It is evident from Figure 3 that annual mean PET calculated using the Hg method (the results from the ensemble mean are shown) is nearly equal to the PM-simulated annual mean PET at nearly all the stations (with available PM-PET data) except San Angelo and El Paso. At El Paso, annual mean PET estimated by the Hg is nearly 450 mm smaller than that computed by the PM. Most of the GCMs grossly underestimated the NSD for temperature at El Paso; their inability to capture the observed variability in temperature likely impacts their ability to simulate PET at this location as well and as such warrants further investigation.

3.3 SPI and SPEI Drought Indices

The 12-month SPI and SPEI drought indices were calculated over the entire study period (1950-2099) and for all three RCPs at all locations. The results from the drought index computations are presented in Figures 4 – 8 and discussed here. Each of these figures shows the SPI and SPEI for a pair of locations grouped alphabetically, such as Abilene and Dallas-Fort Worth, El Paso and Houston, etc. The SPI for all locations (Figures 4-8) under the RCP 2.6 indicates near-normal conditions for the entire duration of the

study period (1950-2099). At Abilene, Dallas-Fort Worth and Lubbock (Figures 4a, 4g and 7a, respectively), a weak upward trend in the SPI can be seen towards the end of the 21st century, likely due to the rebound of precipitation at these locations during the latter half of the century. There is little spatial variation in the SPI under the RCP 4.5 and 8.5, both of which project the dominance of near-normal conditions, albeit with a few brief spells of below average precipitation toward the end of the 21st century. These spells tend to remain relatively short (< 24 months) in duration and mild in intensity (SPI dips only slightly below -1). The variability among the models (the ensemble range) also remains relatively constant across the RCPs and across locations. It is interesting to note that the SPI during the late period largely indicates near-normal conditions across all three RCPs, suggesting that droughts may be temperature-controlled.

The ensemble mean SPEI (Figures 4 – 8) for the RCP 2.6 remains largely within ± 1 SD from the zero mean for all locations. There is a mild upward trend in the SPEI during last two to three decades of the 21st century at Abilene, Dallas-Fort Worth, Lubbock and McAllen (Figures 4d, 4j, 7d and 7j, respectively) corroborating the results of the modified Mann-Kendall test for precipitation at these locations. At the arid to semi-arid locations like El Paso, Laredo and Lubbock (Figures 5e, 6e and 7e, respectively), the RCP 4.5 produces a mild downward trend in the SPEI beginning around the start of the 21st century; this trend appears to stabilize prior to the end of the century but at El Paso, the inter-annual variability is markedly lower compared to Laredo and Lubbock. Despite the slightly downward nature of the trend, the SPEI at these three locations still largely indicates near-normal conditions.

In general, the RCP 8.5 produces a downward trend in the SPEI at all locations beginning around the year 2040 but the magnitude of this trend and the variability among the GCMs show considerable spatial differences. Compared to other locations, Houston and Longview, which are characterized by relatively sub-humid climate, are projected to experience the mildest droughts. As shown in Figures 5l and 6l, the

SPEI at these locations largely remains within ± 1 SD from the zero mean despite a weak downward trend in the last three decades of the 21st century. It is interesting to note that Houston, where statistically significant decreasing trends in precipitation were detected for both the late period and overall (1950-2099) under the RCP 8.5, is still projected to experience only modest drought conditions in the late period. At the other end of the spectrum, the development and persistence of drought (SPEI < -1) is pronounced in arid to semi-arid locations like El Paso, Laredo and Lubbock. As shown in Figure 6f and 7f, the SPEI dips below -1 and largely remains under -1 for the last one to two decades of the 21st century in Laredo and Lubbock. The SPEI patterns in San Angelo (Figure 8f) are almost identical to those in Lubbock, with worsening drought conditions as we move into future. The most severe droughts are projected to occur at El Paso (Figure 5f) where abnormally dry conditions characterize virtually the whole of the last decade of the 21st century. It can also be seen that there is a higher degree of agreement among the GCMs in these projections especially as we near the end of the century. Considering that no statistically significant precipitation trends were detected at El Paso under the RCP 8.5, and that the corresponding SPI shows no evidence of drying, these droughts appear to be a result of increased PET losses, likely due to the pronounced warming produced by the 'business-as-usual' RCP 8.5. On the other hand, decreasing precipitation trends were detected at Laredo, Lubbock, McAllen and San Angelo, suggesting that droughts towards the end of the century under the RCP 8.5 at these locations may be both temperature and precipitation controlled.

The percent of time under each drought index category was calculated to evaluate the patterns in drought frequency over time. A comparison of the fraction of the time periods classified under different drought index categories for Dallas-Fort Worth is presented in Table (vii). There is little variation among the RCPs under the SPI for the historical period and all three emission pathways project the prevalence of near normal conditions for a majority of this time period ($66\% \pm 3\%$ of the time); the same trends were observed in the early and late time periods as well, highlighting the inability of the SPI to capture

temperature-induced or -controlled droughts. The SPEI projects wetter-than-normal conditions (SPEI $\geq$ 1) to prevail longer than drier-than-normal conditions (19-22% vs. 13-8%) for the historical period, with an increasing number of wet periods as we move from RCP 2.6 to RCP 8.5. For the early time period, the SPEI shows little change between the RCPs.

For the late time period, the SPEI shows a drop in the percentage of time under near normal conditions compared to historical and early periods. For this time period, there is a marked increase in the fraction of time spent under abnormally dry conditions from the RCP 2.6 to the RCP 8.5 under SPEI. It can also be seen that the SPEI consistently projects more severe drought conditions than the SPI. Under the RCP 8.5, which produces the highest temperature rise, the SPEI shows almost 33% of the late period to fall under abnormally dry conditions. On the opposite end of the spectrum, only 11% of this time period is projected to experience abnormally wet conditions under the SPEI; this is a pronounced departure from (a) earlier time periods and (b) projections made by the SPI, further highlighting the effect of droughts induced by temperature rise caused by the likes of the RCP 8.5 and the temperature sensitivity of the SPEI. At other locations as well, the highest percentage of time spent under abnormally dry conditions is produced by the RCP 8.5 during the late period, ranging from 42% at El Paso to 21% at Houston (data not shown).

In addition to the percentage of time under each drought index category, the maximum number of consecutive months with drier than average or near-normal conditions, referred to as the maximum drought length (MDL), based on both the SPI and SPEI were also calculated. It can be seen from Figure 9a that there is little variation in the MDL based on the SPI under the RCP 2.6 between the historical, early and late periods; the MDL does not exceed 2 years at any of the chosen locations. The SPEI under RCP 2.6 (Figure 9d) generally projects the longest droughts to occur in the late period with all locations except El Paso projected to experience 20-25 months of drought during this time. Across all locations,

there is a distinct increase in the MDL from the historical to the late period. The SPEI consistently produces longer continuous dry spells at all locations, with Laredo and El Paso projected to experience nearly three years of continuous drought, as shown in Figure 9d.

The SPI under the RCP 4.5 (Figure 9b) indicates minimal variation in MDL across locations and across time periods; these MDLs are also very similar to the ones under the RCP 2.6. The SPEI under RCP 4.5 (Figure 9e), on the other hand, shows a distinct increase in drought severity compared with the RCP 2.6. The late period experiences the most severe MDLs, with El Paso once again ranking first (worst) with nearly 42 months of consecutive drought under RCP 4.5 (Figure 9e). The worst droughts, in terms of the MDL, are projected to occur under RCP 8.5. The SPI under RCP 8.5 (Figure 9c) appears to indicate essentially the same trends as in previous RCPs. The severity of the drought in El Paso, where annual PET is 6-10 times greater than annual P, is remarkable under the SPEI, with over 60 months (5 years) of continuous drought projected. Across much of the state, the most severe droughts are projected to occur in the last decade of the 21st century.

4 Discussion

Evaluation of climate models based on historical observations using a variety of performance metrics often represents the first step in drought impact, planning and adaptation studies. In general, the CMIP5 GCMs perform better in simulating historical temperature than precipitation for the chosen study locations in Texas. The variability in precipitation is consistently underestimated by the GCMs at all locations. As shown in Figures 2c and 2d, the landmark drought of the 1950s is also not well-simulated by the ensemble. There are multiple sources of model errors including uncertainty in parameterizations, biases in mean states of the model and how the GCMs are initialized. There is also uncertainty in observations but these issues have not been addressed here. However, it must be noted that the range of the ensemble (spread between the minimum and maximum) sufficiently captures the observed

temperature, precipitation and drought at all chosen study locations when the entire historical period is considered. Overall, the CCSM4.1 and HadGEM2-AO.1 are able to simulate temperature well across the chosen locations based on the metrics used in this study. However, none of the models, on their own, are able to perform well consistently across different climate divisions when it comes to precipitation; the ensemble mean, instead, appears to be a better alternative, at least for capturing long-term trends. We have used the simple arithmetic mean of the multi-model ensemble in our study whereby each model is assigned the same weight. Other approaches such as reliability ensemble averaging and Bayesian model averaging have been applied (e.g., Duan and Phillips, 2010; Hawkins and Sutton, 2011; Miao et al., 2014) where individual models are weighted based on their performance; these approaches may help reduce some of the uncertainty in projections but as such, these studies agree that performance of any multi-model ensemble is better than a single GCM. It has also been pointed out by Pennell and Reichler (2011) that the uncertainty in future projections may be underestimated by having a smaller number of models. The localized, convective nature of precipitation events across much of the state combined with larger inter-annual variability in precipitation likely result in better model simulation of temperature than precipitation. The relatively poor simulation of precipitation at regional scales has also been reported in the IPCC AR5 (IPCC, 2013) and in regional-level studies such as Mohammed et al. (2015). It must be noted that model inadequacies in simulating historical observations may not necessarily reflect their performance in simulating future climate, given that model projections were not intended to represent climate changes over the short time scales for which observations are available.

While the SPI has been recently adopted as the global standard for drought assessment, the SPEI appears to be emerging as a handy complementary tool, given that it accounts for the effect of temperature changes on future water stress. The role of evaporative demand represented by the PET, which is not captured by precipitation-based indices such as the SPI, is a critical factor in assessing future

533 changes in water resource availability. In this study, we have used the Hargreaves method to estimate
534 PET as it only requires temperature input. Based on comparison with PET estimated using the PM
535 method, it appears that the Hargreaves method is generally sufficient for much of the state except the
536 dry western extreme represented by El Paso. Underestimation of historical PET at El Paso by the
537 Hargreaves method does not necessarily mean that future PET will also be underestimated. However,
538 this finding does add uncertainty to future drought projections for this region. Considering that the
539 worst drying across the chosen locations is also already projected to occur in El Paso, the magnitude of
540 these droughts will only become more severe should PET have been underestimated for future periods
541 as well. The effect of choice of PET method proves critical to our projections when we consider the
542 results from some earlier studies that have used the SPEI in conjunction with climate models in Texas.
543 For instance, Hernandez and Uddameri (2014) have shown the maximum length of abnormally dry
544 months at Laredo to be in excess of 60 months under the SRES A1B scenario applied to two CMIP3
545 models using the Thornthwaite method of PET estimation. We project the same statistic at Laredo to be
546 approximately 40 months under the RCP 8.5. While differences between the models and scenarios
547 certainly impact the resulting projections, the use of the Thornthwaite method appears to overestimate
548 PET with future temperature rise, leading to overestimating drought projections. Recent studies such as
549 Dinpashoh et al. (2011), Jhajharia et al. (2015) have pointed out that increase in temperatures may be
550 offset and even superseded by decrease in wind speed that result in a net reduction in reference
551 evapotranspiration. Hobbins et al. (2004) compared trends in pan-ET and actual ET across the
552 conterminous United States and show that actual ET has 'paradoxically' been increasing across much of
553 the country; they attribute this increase to the effect of the increasing advective budget superseding the
554 effect of decreasing radiative budgets. As such, these studies highlight the need to consider changes in
555 radiative and aerodynamic factors such as wind speed and relative humidity in addition to temperature
556 trends to characterize changes in PET. While the likelihood of future temperature rise and its

subsequent impact on PET has been fairly well-established, potential changes in other climate variables affecting PET are harder to estimate, particularly for regional-based studies.

A detailed investigation of the drought indices indicates that a sweeping generalization cannot be made for a state like Texas due to the spatially diverse nature of its climate. The sensitivity of each location to changes in temperature and precipitation must be taken into account to correctly interpret these drought indices. For instance, it was noted that the climate division represented by El Paso is projected to experience the most severe drying as we move into the 21st century under the RCP 8.5. Considering that the average annual precipitation at El Paso is approximately 150 mm/yr and that there are no significant trends in annual precipitation under the RCP 8.5, future climate variability appears to be entirely driven by temperature fluctuations. On the other hand, drought projections for climate divisions represented by Laredo and McAllen reflect the combined effect of the increasing evapotranspirative losses driven by temperature and decreasing precipitation. Future drying under the RCP 8.5 at Lubbock and San Angelo appear to be very similar, as shown in Figures 7f and 8f, respectively. Although these locations represent different climate divisions, they are both projected to experience a decrease in precipitation overall (from 1950 to 2099). Houston, which represents the wettest climate divisions in our study, is projected to experience very modest future droughts, both in comparison with the drought of record and in comparison with other climate divisions despite decreasing precipitation trends detected under the RCP 8.5. As such, it appears that climatology does not impact the drought projections for this coastal region as much as the lack of availability of the natural resources owing to significant growth and development. Jiang and Yang (2012) who used a set of CMIP3 models under the SRES A1B scenario also note that the East Texas region does not experience drier climate toward the end of the 21st century and attribute this anomalous behavior to the influence of the Gulf of Mexico. It is important to acknowledge and understand the individuality of climate projections for various climate divisions in Texas and incorporate this knowledge into the planning process. It must also be noted that the long-term climate

trends we have presented and discussed in this study are meant to provide a broad representation of future conditions and not a precise assessment of the timing and magnitude of specific events.

As such, water management in a climatologically-diverse state such as Texas is very difficult due to geographical differences in water use and water availability. Unlike the state of California which has recently imposed state-wide stringent water restrictions in response to the ongoing drought (State of California, 2015), the diverse nature of water supply issues in Texas call for management at a more regional or even local level. Texas is also one of the few states that have demands projected to increase significantly in the next few decades (Melillo et al., 2014). The state is at the crossroads of increased demands and decreased supplies and in need for aggressive water management measures. One of the most important water management approaches to meet the projected demand in Texas is redistribution of supplies within and outside the state. This makes the issues with supplies in one region very pertinent to that region and other regions around it. As discussed earlier, urban centers are a dominant factor in future water demand in Texas and an increasing shift from rural to urban water uses will extend this trend well into the future (TWDB, 2007).

Adaptive management can be achieved by (a) encouraging an vigorous campaign for the implementation of policies expected to result in decreasing radiative forcings, (b) changing long-term water supply planning approaches by accounting for uncertainty in future trends and adjusting the planning tools for the potential recurrence of multi-year droughts and (c) revising current water laws and water markets in the state to better manage this resource. Drought management in the state is still approached from the perspective of reacting to an extreme event rather than proactively preparing for water deficits. For instance, imposing water restrictions such as limited water use on lawns on designated days is the norm in most urban areas as a means of drought response. However, a shift in the water market toward pricing usage based on water availability is only recently being viewed as a

more prudent approach. The legal framework governing groundwater allocation also has a major role to play in future adaptive management – at present, many parts of the state allow landowners to drill wells and pump nearly unlimited amounts of water. While groundwater conservation districts (GCDs) have been established to address this issue, many do not require water metering. However, a potential solution to unrestricted pumping by the individual landowner, often referred to as the ‘tragedy of commons’, may lie in the cap and trade system successfully employed in the Lower Rio Grande Valley. Under this system, water rights are allocated by the state and caps are placed on the amount of water that can be pumped; this water can later be traded, creating an opportunity for water markets, which have been shown to produce more realistic water prices.

5 Summary and Conclusions

This paper described the application of an ensemble of CMIP5 models to evaluate drought characteristics in major climate divisions of Texas. As such, there are several unique aspects to this study compared with previous efforts: (a) we have acknowledged the diverse nature of Texas climate and assessed drought characteristics of individual divisions rather than the state as a whole, (b) evaluated the suitability of the CMIP5 GCMs for use in Texas, (c) compared future projections across different RCPs using different indices, and (d) used the entire suite of GCMs as opposed to a small subset. Additionally, we have also demonstrated that some earlier studies may be overestimating 21st century drought intensification in parts of Texas due to the PET estimation methods used.

Overall, the multi-model ensemble projects warmer temperatures for Texas in the 21st century across all three RCPs. There is some respite towards the end of the century under the RCP 2.6 with modest decreases in temperatures across the state and even an upward trend in precipitation in many locations. The ensemble projects decreasing precipitation for semi-arid locations such as Laredo and Lubbock even under the influence of climate policies represented by the RCP 4.5. While decreasing precipitation

627 trends will likely result in reduced streamflows, their impact on groundwater, particularly on the
628 Ogallala, which mainly receives recharge focused through playas collecting rainfall and associated
629 runoff, will be significant. Under the business-as-usual regime simulated by the RCP 8.5, droughts are
630 projected to intensify over the course of the 21st century, with the last decade expected to be the most
631 severe. The intensification of droughts in locations such as Laredo, Lubbock and McAllen under the RCP
632 8.5 is due to a combination of reduced precipitation and increased evaporative demand. In other
633 locations such as El Paso, evaporative demands appear to be singularly responsible for drought
634 intensification. In calculating the evaporative demands, caution must be exercised in selection of the
635 method as it has a significant bearing on the resulting drought projection. As such, it appears that the
636 use of the ensemble or the entire suite of models, as the basis for evaluating future climate is a more
637 prudent approach than employing a single model or a smaller subset of the CMIP5 suite

638 The non-stationarity of climate and its effects on water availability are only beginning to be
639 acknowledged by water planning regions in the state. Recent years have witnessed the impact of large-
640 scale droughts on groundwater in California where no restrictions exist on pumping, allowing farmers to
641 exploit (and deplete, in some cases) this non-renewable resource. Groundwater conservation districts
642 notwithstanding, Texas has taken a laissez-faire approach to groundwater management and planners in
643 the state have a lot of lessons to learn from the recent California drought. Groundwater resources will
644 likely face greater stresses in the future, considering the race to secure rights for their usage; the impact
645 of 21st century droughts on Desired Future Conditions (DFCs) for these aquifers must be thoroughly
646 examined to ensure their sustainability. The projected increase in temperature and evaporation due to
647 climate change has a direct impact on the surface water availability. Therefore, understanding the
648 nature of the impact of climate change on water availability is of significance relevance for effective
649 management of water resources in Texas. Equally important is understanding the surface water and

groundwater dynamic and its intimate relationship with water law, water markets and water pricing to develop optimal solutions for meeting the growing water needs.

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Conflict of Interest

The authors report no conflicts of interest.

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Figure 1

Figure 2

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Figure 9

Table (i) CMIP5 model description and origins.

Model	Model Expansion	Center	Type	Spatial Resolution (lon x lat)	Reference
BCC-CSM1.1	Beijing Climate Center Climate System Model, version 1.1	Beijing Climate Center, China	ESM	2.8 x 2.8	Xin et al., 2012
CanESM2	Second Generation Canadian Earth System Model	Meteorological Administration, China Canadian Center for Climate Modeling and Analysis, Canada	ESM	2.8 x 2.8	Arora et al., 2011
CCSM4	Community Climate System Model, version 4	National Center for Atmospheric Research, United States	AO	1.25 x 0.94	Gent et al. 2011
CESM-CAM5	Community Earth System Model Community Atmosphere Model, version 5	Community Earth System Model Contributors (National Science Foundation, Department of Energy, National Center for Atmospheric Research), United States	AO	1.4 x 1.4	Gent et al. 2011
CSIRO-Mk3.6.0	Commonwealth Scientific and Industrial Research Organization Mark, version 3.6.0	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Centre of Excellence, Australia	AO	1.8 x 1.8	Rotstayn et al., 2010
FGOALS-g2	Flexible Global Ocean-Atmospheric-Land System Model gridpoint, second spectral version	State Key Laboratory of Numerical Modelling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, China	AO	2.8 x 1.6	Bao et al., 2012
FIO-ESM	The First Institute of Oceanography Earth System Model	The First Institute of Oceanography, State Oceanographic Administration, China	ESM	2.8 x 2.8	Qiao et al., 2013
GFDL-CM3	Geophysical Fluid Dynamics Laboratory Climate Model, version 3	NOAA/Geophysical Fluid Dynamics Laboratory, United States	AO	2.5 x 2.0	Donner et al., 2011
GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory Earth System Model with Generalized Ocean Layer Dynamics (GOLD) component (ESM2G)	NOAA/Geophysical Fluid Dynamics Laboratory, United States	ESM	2.5 x 2.0	Donner et al., 2011
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory Earth System Model with Modular Ocean Model 4 (MOM4) component (ESM2M)	NOAA/Geophysical Fluid Dynamics Laboratory, United States	ESM	2.5 x 2.0	Donner et al., 2011

Model	Model Expansion	Center	Type	Spatial Resolution (lon x lat)	Reference
GISS-E2-R	Goddard Institute for Space Studies Model E, coupled with the Russell Ocean Model	National Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies, United States	ChemAO	2.5 x 2.0	Kim et al., 2012
HadGEM2-AO	The Hadley Centre Global Environmental Model version 2	Met Office Hadley Centre, United Kingdom	AO	1.875 x 1.25	Jones et al., 2011
IPSL-CM5A-LR	L'Institut Pierre-Simon Laplace Coupled Model version 5, coupled with NEMO, Low Resolution	L'Institut Pierre-Simon Laplace, France	ChemESM	3.75 x 1.8	Dufresne et al., 2013
IPSL-CM5A-MR	L'Institut Pierre-Simon Laplace Coupled Model version 5, coupled with NEMO, Mid Resolution	L'Institut Pierre-Simon Laplace, France	ChemESM	2.5 x 1.25	Dufresne et al., 2013
MIROC5	Model for Interdisciplinary Research on Climate, version 5	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute and National Institute for Environmental Studies, Japan	AO	1.4 x 1.4	Watanabe et al., 2010
MIROC-ESM	Model for Interdisciplinary Research on Climate, Earth System Model	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute and National Institute for Environmental Studies, Japan	ESM	2.8 x 2.8	Watanabe et al., 2010
MIROC-ESM-CHEM	Model for Interdisciplinary Research on Climate, Earth System Model, Chemistry Coupled	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute and National Institute for Environmental Studies, Japan	Chem-ESM	2.8 x 2.8	Watanabe et al., 2010
MPI-ESM-LR	Max Planck Institute Earth System Model, Low Resolution	Max Planck Institute for Meteorology, Germany	ESM	1.9 x 1.9	Zanchettin et al., 2012
MPI-ESM-MR	Max Planck Institute Earth System Model, Mid Resolution	Max Planck Institute for Meteorology, Germany	ESM		Zanchettin et al., 2012
MRI-CGCM3	Meteorological Research Institute Coupled Atmosphere-Ocean General Circulation Model, version 3	Meteorological Research Institute, Japan	AO	1.1 x 1.1	Yukimoto et al., 2012
NorESM1-M	Norwegian Earth System Model, version 1, intermediate resolution	Norwegian Climate Center, Norway	ESM	2.5 x 1.8	Bentsen et al., 2013
NorESM1-ME	Norwegian Earth System Model, version 1, intermediate resolution with carbon cycle	Norwegian Climate Center, Norway	ESM	2.5 x 1.8	Tjiputra et al., 2012

Table (ii) Drought Categorization schematic.

Drought Index Value	Category
≤ -2	Extremely Dry (ED)
-2 to -1.5	Severely Dry (SD)
-1.5 to -1	Moderately Dry (MD)
-1 to +1	Near-Normal Conditions (NN)
1 to 1.5	Moderately Wet (MW)
1.5 to 2	Severely Wet (SW)
≥ 2	Extremely Wet (EW)

Source: Vicente-Serrano et al., 2010

Table (iii) Normalised standard deviation (NSD) and Mean Absolute Error (MAE) for GCMs in simulating historical (1950-1999) precipitation and temperature at Dallas-Fort Worth (top five models for each metric are highlighted).

Model	Precipitation		Temperature	
	NSD	MAE	NSD	MAE
BCC-CSM1-1.1	0.8509	233.6388	1.0985	0.6995
CanESM2.1	0.8049	223.1328	1.0835	0.6006
CCSM4.1	0.7688	187.6896	1.3501	0.5873
CESM1-CAM5.1	0.7399	237.4620	1.3128	0.8432
CSIRO-Mk3-6-0.1	0.8356	254.4174	1.3143	0.7862
FGOALS-g2.1	0.7510	212.1768	1.2116	0.6146
FIO-ESM.1	0.9192	221.5260	1.0727	0.7024
GFDL-CM3.1	0.9005	232.6296	1.0712	0.6078
GFDL-ESM2G.1	0.8872	227.2812	1.0767	0.6639
GFDL-ESM2M.1	1.1324	225.5760	1.4524	0.8037
GISS-E2-R.1	0.7527	182.3784	1.2738	0.8220
HadGEM2-AO.1	0.7560	245.7834	1.0333	0.5870
IPSL-CM5A-LR.1	0.8920	244.2978	1.3413	0.7529
IPSL-CM5A-MR.1	0.9549	253.8132	1.1978	0.5976
MIROC-ESM.1	0.7109	185.9520	1.1021	0.6693
MIROC-ESM-CHEM.1	0.6914	223.2372	1.0579	0.5967
MIROC5.1	0.9222	233.5302	1.3395	0.7389
MPI-ESM-LR.1	0.8213	221.3172	1.1548	0.8026
MPI-ESM-MR.1	0.8507	237.0144	1.2680	0.7879
MRI-CGCM3.1	0.7296	210.6612	0.9782	0.6109
NorESM1-M.1	0.9343	268.6626	1.1546	0.7842
NorESM1-ME.1	0.8180	184.1166	1.2056	0.6318
Ensemble Mean	0.1723	171.2671	0.4089	0.4520

Table (iv) Annual trends in GCM and observed datasets (statistical significance assessed at $p < 0.05$; significant trends in the observed dataset and models reproducing these trends are highlighted).

Dataset	Precipitation		Temperature	
	p-value	tau	p-value	tau
BCC-CSM1-1.1	0.054	0.189	0.9560	-0.0057
CanESM2.1	0.077	0.107	0.9731	0.0057
CCSM4.1	0.364	0.083	0.0574	0.2555
CESM1-CAM5.1	0.260	0.102	0.7394	-0.0416
CSIRO-Mk3-6-0.1	0.952	-0.006	0.9699	0.0041
FGOALS-g2.1	0.150	-0.141	0.0193	0.2718
FIO-ESM.1	0.384	-0.086	0.0027	0.2931
GFDL-CM3.1	0.214	0.133	0.1503	-0.1004
GFDL-ESM2G.1	0.616	0.050	0.7041	0.0433
GFDL-ESM2M.1	0.071	0.094	0.2284	0.0106
GISS-E2-R.1	0.639	0.047	0.8019	-0.0253
HadGEM2-AO.1	0.509	-0.051	0.7478	-0.0367
IPSL-CM5A-LR.1	0.063	-0.182	0.0002	0.4237
IPSL-CM5A-MR.1	0.432	-0.078	0.2220	0.1200
MIROC-ESM.1	0.023	0.223	0.6276	-0.0482
MIROC-ESM-CHEM.1	0.850	0.022	0.8803	-0.0155
MIROC5.1	0.270	-0.109	0.1694	0.1527
MPI-ESM-LR.1	0.726	-0.019	0.1405	0.1576
MPI-ESM-MR.1	0.779	0.024	0.1322	0.1478
MRI-CGCM3.1	0.604	0.051	0.0592	-0.1510
NorESM1-M.1	0.651	0.045	0.9466	-0.0073
NorESM1-ME.1	0.370	0.073	0.8540	0.0188
Ensemble Mean	0.040	0.094	0.1405	0.2212
Observed	0.042	0.146	0.3236	0.0971

Table (v) Spatial trends in observed and GCM-projected precipitation (only statistically significant trends at $p < 0.05$ are shown; upward (red) arrows indicate increasing trends and downward (blue) arrows indicate decreasing trend; Dallas-Fort Worth is abbreviated as DFW).

Location	Historical		Early			Late			Overall (1950-2099)		
	Observed	Ensemble Mean	RCP2.6	RCP4.5	RCP8.5	RCP2.6	RCP4.5	RCP8.5	RCP2.6	RCP4.5	RCP8.5
Abilene	-	-	-	-	-	↰	-	-	↰	-	-
DFW	↰	↰	-	-	-	-	-	↗	↰	-	-
El Paso	↰	-	-	-	-	-	-	-	-	↗	-
Houston	↰	-	-	↰	-	↰	-	↗	↰	-	↗
Laredo	-	-	-	↗	↗	-	↗	-	-	↗	↗
Longview	-	-	-	-	-	-	-	↗	-	-	-
Lubbock	-	-	-	-	-	↰	-	-	↰	↗	↗
McAllen	↰	↰	-	↗	-	-	-	-	-	↗	↗
San Angelo	-	-	-	-	-	↰	-	-	↰	-	-
San Antonio	↰	↰	-	-	-	-	↗	-	-	↗	↗

Table (vi) Trends in observed and GCM-projected temperature (only statistically significant trends at $p < 0.05$ are shown; statistically significant increasing trends are detected for the early, late, and overall time periods at all locations for the ensemble mean and are hence not shown; upward (red) arrows indicate increasing trend; Dallas-Fort Worth is abbreviated as DFW).

Location	Historical	
	Observed	Ensemble Mean
Abilene	-	-
DFW	-	-
El Paso	-	-
Houston	-	-
Laredo	↑	↑
Longview	-	-
Lubbock	-	↑
McAllen	↑	↑
San Angelo	↑	↑
San Antonio	↑	↑

Figure Captions

Figure 1 (a) Climate divisions of Texas; (b) annual average precipitation (c) annual average maximum temperature and (d) annual average minimum temperature.

Figure 2 Observed vs. GCM-projected: (a) temperature, (b) precipitation, (c) SPI and (d) SPEI for Dallas-Fort Worth.

Figure 3 Comparison of 1950-1999 average PETs (in mm) estimated using the Hargreaves method (for GCM-projected data) and PETs derived using the Penman-Monteith method sourced from the Texas ET network.

Figure 4 Ensemble-projected drought indices for: (a) - (f) Abilene and (g) - (l) Dallas-Fort Worth.

Figure 5 Ensemble-projected drought indices for: (a) - (f) El Paso and (g) - (l) Houston.

Figure 6 Ensemble-projected drought indices for: (a) - (f) Laredo and (g) - (l) Longview.

Figure 7 Ensemble-projected drought indices for: (a) - (f) Lubbock and (g) - (l) McAllen.

Figure 8 Ensemble-projected drought indices for: (a) - (f) San Angelo and (g) - (l) San Antonio.

Figure 9 Maximum Drought Length (MDL) for the study areas.

Table Captions

Table (i) CMIP5 model description and origins.

Table (ii) Drought categorization schematic.

Table (iii) Normalised standard deviation (NSD) and Mean Absolute Error (MAE) for GCMs in simulating historical (1950-1999) precipitation and temperature at Dallas-Fort Worth (top five models for each metric are highlighted).

Table (iv) Annual trends in GCM and observed datasets (statistical significance assessed at $p < 0.05$; significant trends in the observed dataset and models reproducing these trends are highlighted).

Table (v) Spatial trends in observed and GCM-projected precipitation (only statistically significant trends at $p < 0.05$ are shown; upward (red) arrows indicate increasing trends and downward (blue) arrows indicate decreasing trend; Dallas-Fort Worth is abbreviated as DFW).

Table (vi) Trends in observed and GCM-projected temperature (only statistically significant trends at $p < 0.05$ are shown; statistically significant increasing trends are detected for the early, late, and overall time periods at all locations for the ensemble mean and are hence not shown; upward (red) arrows indicate increasing trend; Dallas-Fort Worth is abbreviated as DFW).

Table (vii) Percent of time under each drought category for Dallas-Fort Worth: (a) SPI and (b) SPEI (Percent of time under Near Normal conditions is highlighted; explanation of acronyms of drought categories is presented in Table (ii)).