Unprecedented drought challenges for Texas water resources in a changing climate: what do researchers and stakeholders need to know?

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Abstract

Long-range water planning is complicated by factors that are rapidly changing in the 21st century, including climate, population, and water use. Here, we analyze climate factors and drought projections for Texas as an example of a diverse society straddling an aridity gradient to examine how the projections can best serve water stakeholder needs. We find that climate models are robust in projecting drying of summer-season soil moisture and decreasing reservoir supplies for both the eastern and western portions of Texas during the 21st century. Further, projections indicate drier conditions during the latter half of the 21st century than even the most arid centuries of the last 1,000 years that included megadroughts. To illustrate how accounting for drought non-stationarity may increase water resiliency, we consider generalized case studies involving four key stakeholder groups: agricultural producers, large surface water suppliers, small groundwater management districts, and regional water planning districts. We also examine an example of customized climate information being used as input to long-range water planning. We find that while stakeholders value the quantitative capability of climate model outputs, more specific climate-related information better supports resilience planning across multiple stakeholder groups. New suites of tools could provide necessary capacity for both short and long-term, stakeholder-specific adaptive planning.

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To illustrate how accounting for drought non-stationarity may increase water resiliency, we consider generalized case studies involving four key stakeholder groups: agricultural producers, large surface water suppliers, small groundwater management districts, and regional water planning districts. We also examine an example of customized climate information being used as input to long-range water planning. We find that while stakeholders value the quantitative capability of climate model outputs, more specific climate-related information better supports resilience planning across multiple stakeholder groups. New suites of tools could provide necessary capacity for both short and long-term, stakeholder-specific adaptive planning.

1. Introduction

Climate projections for the 21st century portray "*unprecedented*" drought risk for the U.S. Southwest and Great Plains (Cook et al., 2015). This presents unprecedented challenges for water managers and stakeholders, as well as unprecedented data needs. What information does the existing state of science provide that is relevant to water planning? What new information is critical for water planning? How can the gap between the available and needed information be closed? The purpose of this paper is to confront these questions for a diverse society straddling an aridity gradient, using issues arising in the state of Texas as an example, and informed by an ongoing multi-year project to facilitate knowledge co-production among scientists and stakeholders.

Texas is one of the fastest growing states in the nation, with population expected to increase from 29.5 million in 2020 to 51 million in 2070 (TWDB, 2017). Further, the state is located in a sub-humid to semi-arid environment that is vulnerable to changes in water availability resulting from global climate change. There is significant variation in the extent of water stress across Texas, historically associated with the '100th Meridian' (the line of 100^{o}W longitude), which approximates the location of the wet-dry (east-west) transition across the center of the state (Powell, 1897; Seager et al. 2018a, b). Surface and groundwater resources are essential Texas water supplies, and the strong east-west climatic gradient drives a range of supply to demand ratios (Seager et al. 2018a, b). Damming and water withdrawals from rivers threaten both terrestrial and coastal ecosystems that provide habitat to threatened and endangered species and support coastal communities and economies (Montagna and Kalke, 1992). The state's historical water use has been primarily for agricultural purposes. Population growth is now driving a shift in water prioritization from rural to urban areas. Irrigation and municipal use are projected to comprise 51% and 28%, respectively, of water need in 2020, compared with 36% and 39% in 2070 (TWDB, 2017).

The uncertainty in future water availability is substantial (Taylor et al., 2013; Schewe et al., 2014). Texas, like a number of other regions in the world, is currently water-stressed (Oki and Kanae, 2006). Increasing temperatures, decreasing water availability, and increasing heat and precipitation extremes will further exacerbate known challenges to water resilience (Kloesel et al., 2018), which for the purposes of this study denotes the ability to satisfy water needs under a range of changes in supply and demand, including those driven by changes in population and climate.

Texas follows a regional approach to water planning, with a five-year planning cycle beginning at the local level, then expanding to regional water planning groups, and concluding at the state level (Bruun, 2017). The most recent Texas State Water Plan assesses water supply and demand over a 50-year horizon and provides a cost analysis of implementing management strategies designed to meet demand where and when it exceeds supply (TWDB, 2017). Texas water planning is based on the goal of having an adequate supply of water to meet the needs of future water users even if the worst drought in history, the "drought of record", returns. In most parts of the state, the drought of record is the six-year drought of the 1950's, the worst drought in the 125 years of the instrumental record (Cook et al., 2019; McGregor, 2015; Moore, 2005; Nielsen-Gammon, 2012).

The state water plan, like much water planning throughout Texas, is based on a rear-view mirror approach that focuses on historical data and patterns of drought. This record-driven approach has the virtue of grounding modeling and planning around actual measured and monitored droughts, and the five-year updates allow it to respond to recent climatic changes. This top-level state water plan, however, does not take into consideration potential declines in water supply related to future climate change. For example, the state plan reports only a 3% decrease in surface water availability from 2020 to 2070, which is related to reductions in reservoir storage that will be induced by infilling of the reservoirs with sediment. The plan states that forecasts of future changes in water resources due to climate change are not used due to a lack of reliable, usable estimates of such changes. In the current state planning system, planners can opt to include "extra" water supplies to guard against droughts worse than the drought of record. Yet no tools are provided to assist in such planning, and the political hurdle of explicitly addressing climate change presents its own challenge (Kirchhoff and Dilling, 2016). On the other hand, if climate change were to reduce drought risk, some future planned infrastructure may be unnecessary.

Here we analyze the state of climate in Texas from the combined perspective of past, present, and future changes. We then use projections of future climate to consider possible changes in stakeholder-relevant parameters, such as soil moisture and reservoir storage (for agriculture and resource management stakeholders, respectively). The relevance of future projections is then assessed both from the perspective of hypothetical stakeholders to identify the extent to which information is actionable, incompatible, or unavailable, as well from the perspective of one municipality that attempted to bridge the gap. We envision this as a first step in an on-going process of co-production of knowledge between researchers and stakeholders, consistent with the recommendations of Moss et al. (2019). We anticipate that stakeholders will eventually be able to draw upon readily available projections of relevant parameters to inform local management and planning decisions, with the information contained in those science-based projections driven in part by their actual usefulness for decision-making. We also intend that scientists and stakeholders elsewhere can use the Texas situation to identify knowledge, research, and communication gaps in their own communities.

2. The Texas Climate Context

2.1 The Paleoclimate Perspective

Climate change leaves its mark on Texas in many ways. These marks, based on biological, chemical, and physical effects of climate, can be used to reconstruct changes in Texas climate prior to the late 1800s (Musgrove et al., 2001; Banner et al., 2007, Cleaveland et al., 2011, Wong et al., 2015, Livsey et al., 2016, Baker et al., 2019).

Although they occurred at a much slower pace, the warming and associated shifts in precipitation that occurred over the past 20,000 years may provide a valuable analogue to projected 21st century warming. Growth rates of speleothems across central Texas generally increased during past glacial periods, indicating that Texas was wetter during these cold periods (Musgrove et al., 2001). Texas speleothem growth accelerated episodically with the onset of a major glacial melting period that lasted from 14,700 to 12,800 years ago (Feng et al., 2014; Miller and Banner, 2018). This suggests that warming also provides a temporary increase in moisture, and exemplifies the complexities in the response of Texas climate to global changes.

The transition to interglacial conditions heralded a warmer and drier climate in Texas, brought an increase in extremes in drought-flood cycles, and led to a significant reduction in soil thickness (Toomey et al., 1993; Cooke et al., 2003). A synthesis of proxy-derived climate reconstructions suggests that between 7,000 and 3,000 years ago Texas apparently was even warmer, but with differing indicators on the amount of effective moisture present (Wong et al., 2015). Within the past 3,000 years, warmer Northern Hemisphere climates corresponded to drier conditions in South Texas, but this may have been due to Atlantic Ocean variability rather than a direct temperature-aridity relationship (Livsey et al., 2016; McCabe et al., 2004).

Tree ring studies are another valuable proxy for understanding the drought history of Texas over the past 1,000 years. Tree-ring studies reveal droughts lasting a decade or longer ('megadroughts') that occurred in Texas each century over the past 1,000 years (Banner et al., 2010; Cleaveland et al., 2011; Cook et al., 2015). In the most intensive drought reconstruction for Texas to date, Cleaveland et al. (2011) found that there were intervals with more severe and/or more protracted drought than the 1950's drought of record. Such paleoclimate events can be used to explore water supply vulnerabilities on different time scales and levels of severity than those encapsulated in the drought of record.   As discussed in Section 2.3, however, future droughts may differ from past droughts in fundamental ways.

2.2 The Instrument Record

In Texas, historic air temperatures exhibit trend variations that broadly match global air temperature trends, with a general increase during the first part of the 20th century, a decline between about 1955 and 1975, and an increase thereafter (Fig. 1). Texas temperatures are more temporally variable than globally-averaged temperatures. Temperature increases have been observed in all parts of the state, with the greatest increases in West Texas (USGCRP, 2017).

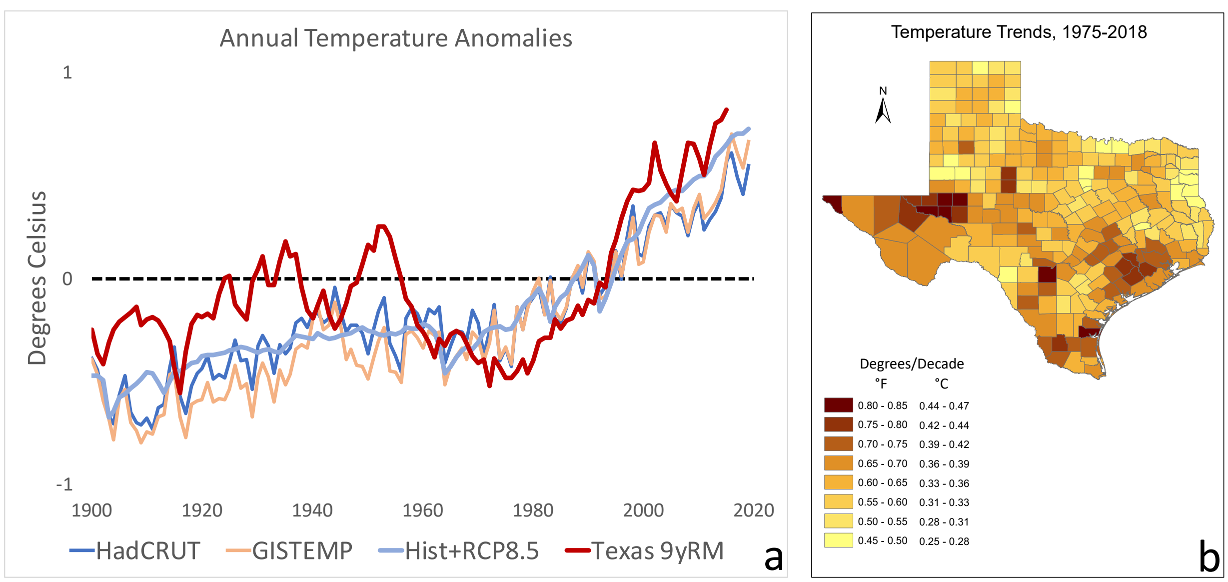
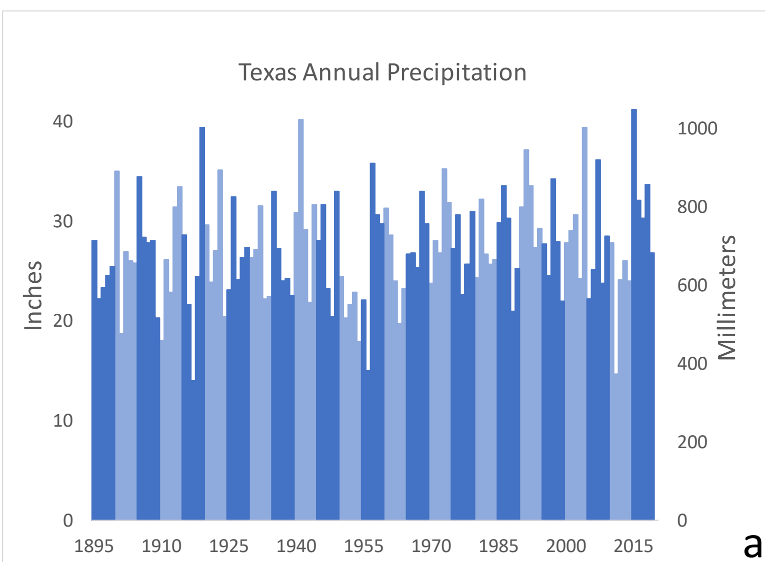


Figure 1. a.) Annual air temperature anomalies in Texas compared to observed and simulated average global temperature anomalies. Anomalies are relative to a 1980-1999 baseline. Global analyses are HadCRUT4 (Morice et al., 2012) and GISTEMP (Hansen et al., 2010). Texas temperature anomalies are from nClimDiv data (Vose et al., 2014). CMIP5 ensemble mean simulations (one ensemble member for each model) include historic runs to 2005 and RCP8.5 runs thereafter, obtained from the Royal Netherlands Meteorological Institute (KNMI) Climate

Explorer (www.climexp.knmi.nl). b.) Map of decadal rate of change of annual average temperature between 1975 and 2018 for each county, according to ordinary least-squares regression on nClimDiv data. The range is 0.45-0.85 °F per decade, or 0.25-0.47 °C per decade.

Texas precipitation is highly variable. Some of this variability is driven by large-scale weather and climate patterns, such as El Niño and La Niña (Hoerling et al., 2013, Cheng et al., 2018), while much of the variability during the warm season is due to the somewhat random distribution of thunderstorms and tropical disturbances. Overall there has been a long-term upward trend in precipitation in Texas in all seasons, averaging about 8.5% per century (Fig. 2). The largest trends have been in central and eastern Texas, while parts of west Texas have seen a decrease (for broader context, see USGCRP, 2017). However, natural variability commonly produces statewide variations of precipitation of 20% or more on a decadal scale.



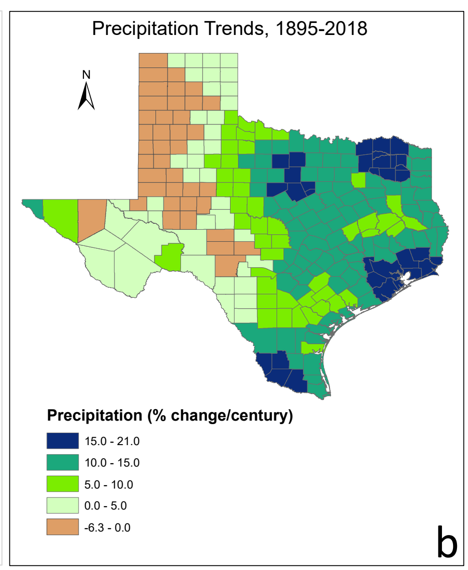


Figure 2. a.) Average annual rainfall in Texas from 1895 to present, according to nClimDiv data (Vose et al., 2014). b.) Map of annual precipitation trend (% change per century) according to ordinary least-squares regression for the period 1895-2019, using nClimDiv data.

There has also been an upward trend in extreme precipitation at a variety of time scales (USGCRP, 2017). On a global basis, the increase of extreme rainfall is systematically larger than the increase of overall rainfall, because different processes are driving the changes. This leads to an increase of precipitation variability as well (Pendergrass et al., 2017). We note that an overall increase in rainfall would lead to greater surface and groundwater supply, while a tendency for rain to be more intense would separately favor runoff (and hence surface water supply) over infiltration in those locations where the rain rate regularly exceeds the infiltration rate.

2.3 Climate Interactions Affecting Drought

While precipitation variability is one important driver of change in soil moisture availability, it is by no means the only influence on the surface moisture budget. Soil moisture is also affected by the rate at which water leaves the soil. Downward percolation into aquifers depends on local soil conditions, while the upward flow of water into the atmosphere is affected by many atmospheric and vegetative processes (Bonan, 2016). Even if the amount of water vapor increases to keep pace with temperature, higher temperatures lead to greater evaporation rates (Penman, 1948). Transpiration from plants is also increased, although plants can regulate their transpiration. Increased CO_2 levels allow plants to keep their stomata less open, leading to slower water loss, which may temper soil moisture losses (Sellers et al., 1996; Swann et al., 2016; Lemordant et al., 2018). Combined changes in CO_2, temperature, and rainfall also lead to changes in biomass and plant species distribution, which in turn can affect soil moisture (Tietjen et al., 2016).

This complicated interplay of moisture parameters makes it difficult to develop a universal drought metric and requires contextual characterization of drought conditions. Agricultural drought, for example, is ultimately a matter of major root-zone soil moisture deficiencies that adversely affect agricultural production (Wilhite and Glantz, 1985). This contextual characterization is a description of soil moisture and is insensitive to whether or not insufficient rainfall can be supplemented by irrigation. Hydrological drought, on the other hand, involves weather-driven reductions in streamflow and reservoir storage that adversely affect human water supply and ecosystems (Wilhite and Glantz, 1985). Some processes favor drought of both types, while others favor one over the other. Without changes in variability, for example, reduced rainfall lowers both soil moisture and runoff. But increased rainfall variability can lead to widespread increases in soil moisture deficits even if overall runoff becomes greater (Dai et al., 2018).

These complex interactions have inspired a variety of drought indices. The Palmer Drought Severity Index (PDSI; Palmer, 1965) is widely employed in observational, modeling, and paleoclimate studies (Cook et al., 2010, 2015; Williams et al., 2015). The PDSI is a commonly used drought index in part because it is sensitive to fluctuations in precipitation that are rapid enough to cause agricultural drought and can be long-lasting enough to cause hydrologic drought. However, the PDSI in an individual season is not necessarily representative of annual average conditions. Springtime snapshots of PDSI are relevant to plants that have a limited growth season, but long-term water supply in large basins is often dependent on a few irregularly-occurring large runoff rain events that might occur any time of year or even skip a year. While tree ring growth is sensitive to soil moisture and (sometimes) streamflow, it cannot identify the occurrence of individual rainfall events that produce the greatest amount of runoff and reservoir resupply.

Also, while the PDSI incorporates temperature, it does so crudely, and different implementations differ in their sensitivity to rising temperatures. A more comprehensive measure of agricultural drought is made through quantifying soil moisture deficit (Keyantash and Dracup, 2002). Ultimately, for agricultural drought, a model of plant response to moisture conditions is desirable because it addresses the phenomenon at the core of agricultural drought. Likewise, hydrological drought severity is best evaluated using variables such as streamflow and reservoir storage.

2.4 Drought Projections

Temperature is expected to continue increasing in Texas at or greater than the global mean rate of increase, particularly during droughts (Chiang et al., 2018), although the sensitivity of drought to long-term temperature change is a matter of considerable uncertainty (Mukherjee et al., 2018). Precipitation intensity is also projected to continue increasing, as a warmer Gulf of Mexico provides more water to the lower atmosphere. Individual models disagree on the sign and spatial gradient of the overall climate-driven precipitation change (Jiang and Yang, 2012; Maloney et al., 2014; Easterling et al., 2017), with a general tendency toward less precipitation in the future. There is more consensus regarding summertime rainfall, with climate models consistently projecting less precipitation in the future due to processes known to be important in driving present-day summertime drought in Texas (Bukovsky et al., 2017; Ryu and Hayhoe, 2017). Ventakaraman et al (2016) has found increasing drought frequency and severity toward the latter half of the 21st century specific to Texas in CMIP5 ensemble-mean projections.

Cook et al. (2015) compared drought as reconstructed over the last millennium by the North American Drought Atlas to drought conditions projected under higher (RCP 8.5, Representative Concentration Pathway; van Vuuren et al., 2011; see Hayhoe et al., 2017 for more information on scenarios and models) and lower (RCP 4.5) carbon emission scenarios. Cook et al. found that projected drought conditions are unprecedented over the past 1000 years in almost all CMIP5 global climate models (GCMs) analyzed under RCP 8.5 and in a majority under RCP4.5 (Cook et al., 2015) in both the Central Plains and southwestern United States. A significant portion of the present-day multidecadal drought in the southwestern United States is already being driven by increased temperatures (Williams et al. 2020).

Following Cook et al.'s (2015) analysis of the Central Plains, we present RCP 8.5 projections for west Texas and east Texas, with the division along the 100th Meridian as discussed above (Fig. S1). Details of the analysis are discussed in the Supplemental Material. For both west and east Texas, most models and indicators show significant shifts towards drier conditions by the latter half of the 21st century (Fig. 3; Figs. S3 and S4), consistent with broader mid-latitude trends (Douville and Plazzotta, 2017). This drying occurs from the combined influence of declining precipitation and increased evaporative demand from a warmer atmosphere (e.g., Cook et al., 2014). Within most models, the sign and relative significance of change is similar across the three indicators, though there is substantial model spread (Fig. 4).

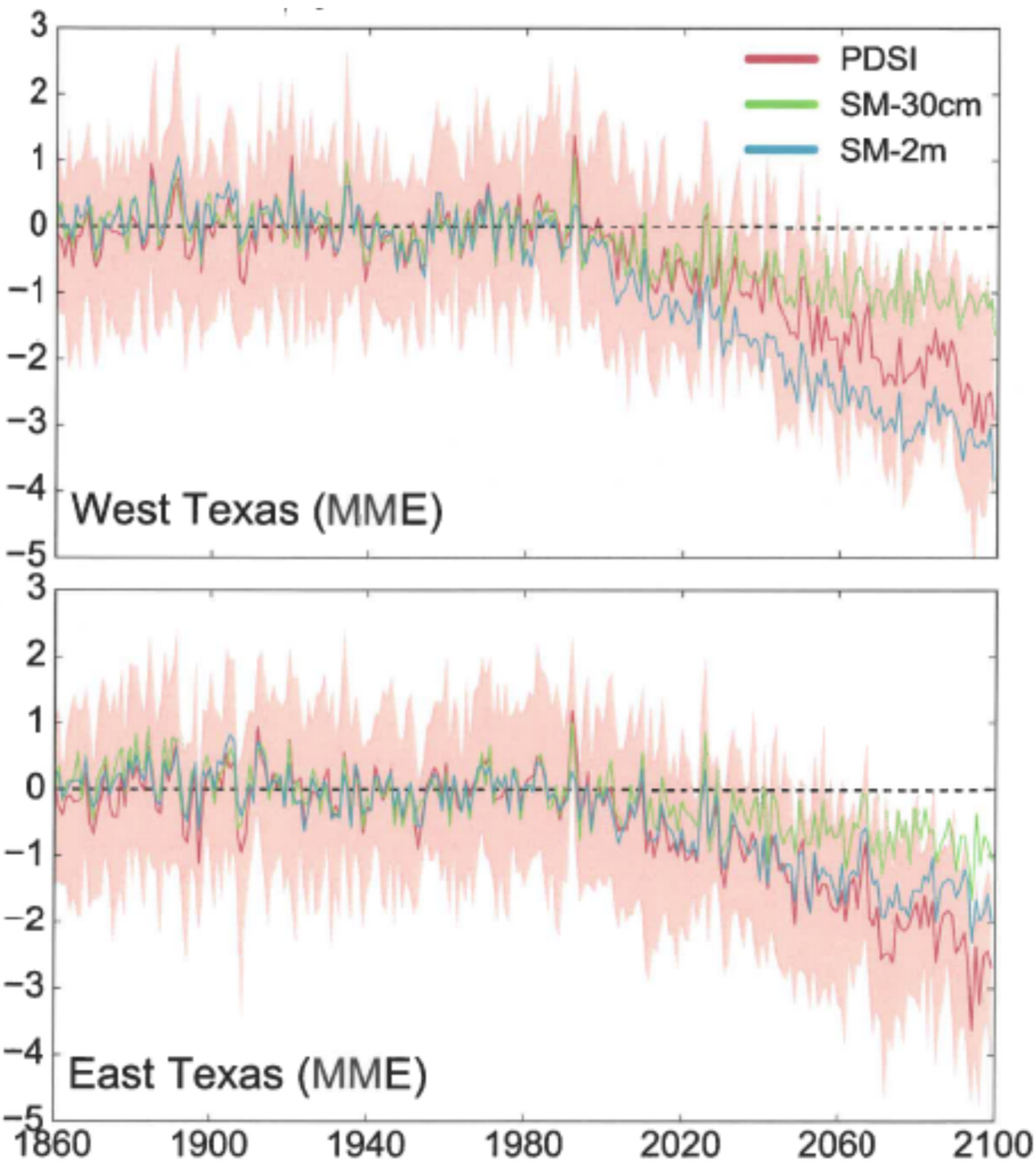


Figure 3. Multi-model ensemble simulations of historic and future projected (RCP8.5) standardized Palmer Drought Severity Index (PDSI) and standardized soil moisture anomalies (SM) at 30cm and 2m depth for West Texas (top) and East Texas (bottom).

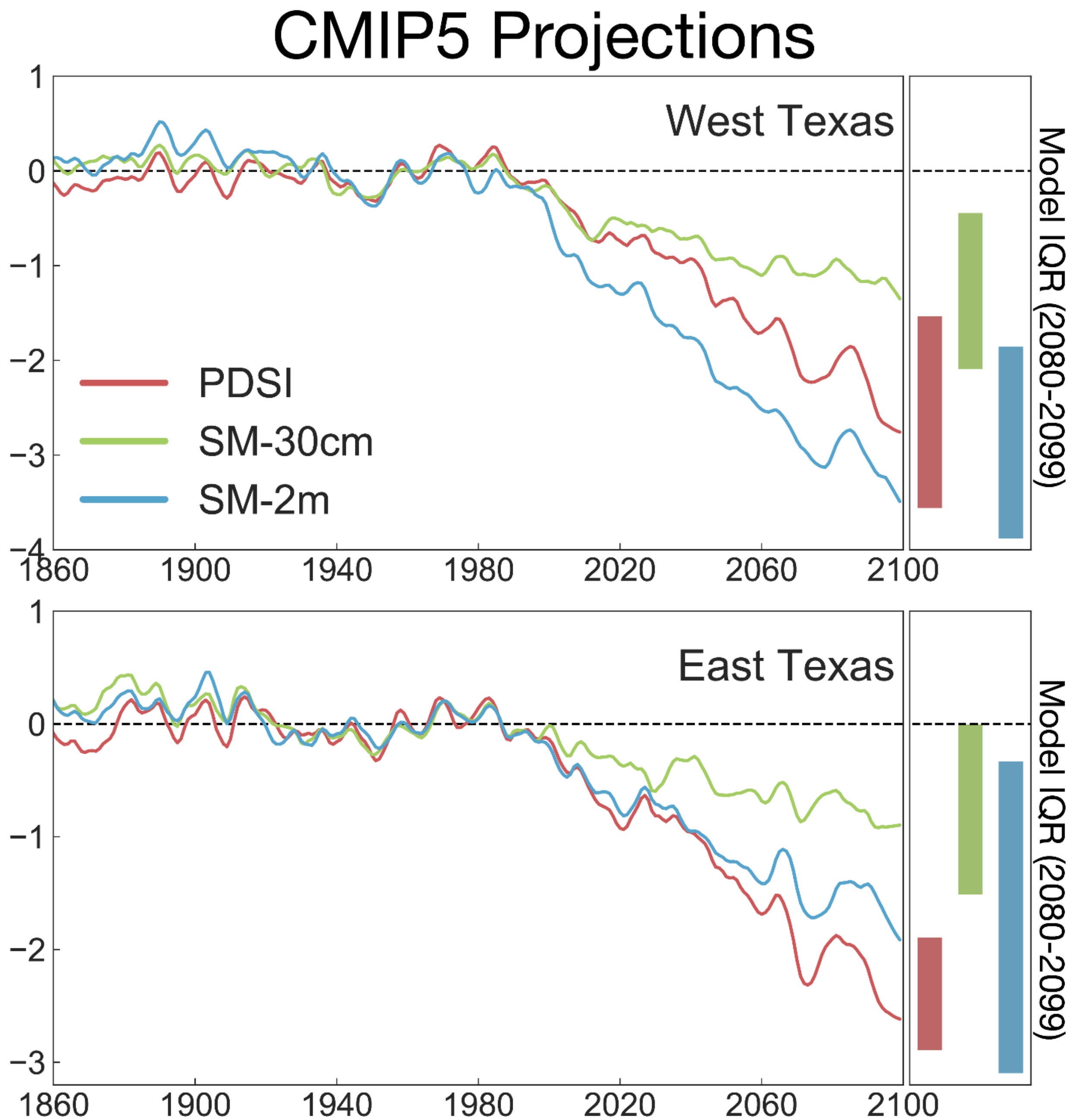


Figure 4. Left Panels: Ten-year smoothed (lowess filter) ensemble average time series of regional PDSI and standardized soil moisture from the CMIP5 historical+RCP 8.5 simulations (1860-2099). Right Panels: Interquartile range (IQR) across the model ensemble of multi-decadal average PDSI and standardized soil moisture for the end of the 21st century (2080-2099).

The multi-model average values of all three indicators are significantly drier by the latter half of the 21st century (Fig. 3), and this is also reflected in the probability distributions calculated from pooling all years across all models in the multi-model ensemble (Fig. S5). The least drying under RCP 8.5 occurs in the near surface SM-30 cm soil moisture. Median PDSI is also negative, while drying in SM-2m is more severe in west Texas than east Texas. To provide some perspective, these results indicate that even for the most optimistic case (SM-30cm), *median* conditions during the latter half of the 21st century in both regions will approach the intensity of a moderate 20th century drought event. In all cases, the multi-model ensemble suggests drier conditions during the latter half of the 21st century than even the most arid centuries that were characterized by megadroughts (1100-1300) (Fig. S6).

Differences in projected drought severity between the soil moisture indicators shown in Figure 3 are likely due to several factors. CO2-induced increases in vegetation water use efficiency (Morison, 1985; Milly and Dunne, 2016) affect climate models' soil moisture, but are not included in PDSI (Swann et al., 2016), and they are affected differently by atmospheric drying (Ficklin and Novick, 2017). The greater intensity of relative drying in SM-2m versus SM-30cm is reversed when absolute moisture changes, rather than relative moisture changes, are considered (e.g., Berg et al., 2017), since deeper soils have less interannual moisture variability. The precipitation declines in the CMIP5 models in Texas are stronger in winter toward the southwest and stronger in summer toward the northeast (Berg et al., 2017; Easterling et al., 2017), with wintertime precipitation having greater opportunity to soak deeply and persist in the larger SM-2m soil moisture pool. Ultimately, these differences across soil moisture and the PDSI make drought projections sensitive to the specific drought metric used, with no single metric being best for all applications. Furthermore, none of those metrics discussed above are designed to identify changes in streamflow, groundwater recharge or reservoir storage.

Regardless of differences between indicators and across models, the drying of summer-season soil moisture appears as a remarkably robust response in climate change projections for Texas. This includes broad coherence across various drought indicators, and a largely consistent response across models in the ensemble. Further, this points to a fundamental shift in soil moisture for the region to a drier state comparable to, or even exceeding, the driest centuries of the last 1000 years. The consequences for vegetation, however, remain an open question (Schwantes et al., 2017; Swann, 2018; Scheff, 2018).

3. Translation of climate data to stakeholder relevant parameters

Healthy ecosystems, rapidly growing municipalities, and energy and agricultural production are key factors for sustaining population and economic growth within Texas. The availability of fresh water is key to these activities, and this availability is likely to be affected by the impact of climate change on both drought and extreme precipitation events and associated storms. The worst single year of drought across the state occurred in 2011. This event left the state with 7.6 billion dollars in agricultural and livestock losses, 301 million dead trees (6.2% mortality statewide; Moore et al., 2016), and many dried-up lakes and rivers (Nielsen-Gammon, 2012). Combining climate change with the projected population growth discussed above, it is likely that Texans will face unprecedented challenges to the resilience of their water supply that depend on whether a given location depends primarily on surface water or groundwater.

3.1 Potential changes in the Texas water budget

Texas contains 15 major river basins, most of which reside solely within the state. Most of these rivers meander from the arid northwest to the wetter southeast to the Gulf of Mexico. Physics-based distributed hydrologic models are commonly used to reconstruct long term historical records at a large scale (Nijssen et al., 2001; Zhang et al., 2014). The quality of the product depends on how well the model can be calibrated and validated. Products over the U.S. generally have not shown good performance within most Texas river basins (Maurer et al., 2002; Livneh et al., 2013; Oubeidillah et al., 2014; Witham, 2015; Samady, 2017). The Variable Infiltration Capacity (VIC) model (Liang et al., 1994) was recently calibrated and validated against observed streamflow over ten major Texas river basins (Lee et al., 2017). The simulated soil moisture was also evaluated using observations from the NASMD. Driven by gridded meteorological forcings obtained from Livneh et al. (2013), the hydrologic dataset includes daily values for a complete set of water and energy budget terms (e.g., precipitation, evapotranspiration, soil moisture at three layers, surface runoff, baseflow, latent heat, and sensible heat) at $1/8^{th}$-degree resolution from 1918 to 2011. The potential benefits of this dataset toward future planning of Texas water resources are two-fold. First, the calibrated model can be forced with future climate outputs from GCMs to project water and energy budget terms under various emission scenarios. Second, the long-term hydrologic record can provide a point of reference for model projections and enable process-based understanding of changes in water availability.

To make the modeled future hydroclimatological results relevant to decision making, thorough uncertainty quantification is imperative. The uncertainties associated with these hydrologic projections are primarily from five sources: RCP scenarios, GCMs, downscaling methods that infer future local weather conditions from broader-scale simulated trends, hydrologic models, and natural variability. The different RCPs lead to very different outputs (IPCC, 2013; Jones et al., 2013). Because of their coarse resolutions and different physical/computational algorithms, GCMs simulate different climate outcomes under the same scenarios (Giorgi and Mearns, 1991; Barnett et al., 2006; Teng et al., 2012). Before applying hydrologic models, the GCM outputs first need to be downscaled, which means that the outputs need to be converted to data with much higher spatial resolution (Wood et al., 2004). Both statistical downscaling and dynamic downscaling are commonly used. Statistical approaches, which rely on historical relationships between large-scale and local conditions, are computationally efficient, while dynamic downscaling methods require substantial computing resources. Dynamical downscaling uses regional-scale climate models to more directly simulate the relevant physical processes, often with statistical downscaling of the regional-scale model output. Hydrologic modeling uncertainties are attributable to uncertainties in forcing inputs and model setup (e.g., structure and parameters). Natural variability means that actual conditions will differ year to year from even a perfect climate simulation.

To translate climate and hydroclimate projections into information relevant to water management, each of these uncertainty sources needs to be assessed (for each river basin) and communicated to the stakeholder in an effective manner (Harrison et al., 2013; Cartier, 2019). Even if all sources of uncertainty are clearly communicated, the degree of uncertainty in current hydroclimatological results may limit their usefulness in many cases. But water management decisions are always made in a climate of uncertainty, so it is even more crucial in a changing climate to emphasize the importance of robust, no-regrets solutions and adaptive management that allows for new information to be periodically incorporated.

3.2 Adapting reservoir management to a changing climate

Reservoirs in Texas are essential for providing water supply and for mitigating floods. Texas used about 5.9 million acre-feet of water in 2017, which accounted for approximately 43% of total use in 2017 (TWBD, 2019). Across the Brazos and Colorado river (Texas's Colorado river, not the one that drains the southwestern US) basins of West Texas, Dawson et al. (2015) find that reservoir inflow and storage has generally decreased, eutrophication generally increased, and water temperature has generally increased. These trends appear to reflect a combination of local human influence, changes in local hydrology, and long-term climate trends (Dawson et al. 2015; Gelca et al. 2015).

A warmer climate with more variable precipitation poses an unprecedented challenge for reservoir managers supporting the growing population and economy. Various studies use the output from climate model projections as input to hydrological models to investigate climate change impacts on water quality and supply (Milly et al., 2005; Haddeland et al., 2014; in Texas, Gelca et al., 2015). The reservoir schemes in such models are typically simplified for use at a large scale (e.g., continental or global). To produce informative results suitable for local management, the reservoir modules in such hydrological models should be able to represent the real, predefined, complex operational rules, such as when and how rapidly water is released from the flood pool. To close this gap, Zhao et al. (2016) implemented a multi-purpose reservoir module into the Distributed Hydrology Soil Vegetation Model (DHSVM; Wigmosta et al., 1994) and tested it for Lake Whitney (one of the largest reservoirs in Texas). Results suggest that the ability to provide water during drought conditions is especially sensitive to rules for floodwater storage, which means this modeling tool can be used to evaluate different flow regulation options. Developing such options will help promote water resilience under future environmental changes. Aside from changes in water storage, Gelca et al. (2015) found that climate change would likely increase water temperatures, specific conductance, and levels of sulfate and chloride while decreasing dissolved oxygen levels and pH, many of which would affect the quality of water available for human consumption and recreation.

Knowledge about future reservoir storage, and the associated uncertainties—both for individual reservoirs and for a system at basin scale—is prerequisite for effective planning. Zhao et al. (2018) modeled the surface water supply for Dallas as an example to demonstrate this concept. First, the DHSVM model (with its reservoir module) was calibrated and validated over the historical period. Then, the model was driven by eight downscaled CMIP5 GCM outputs (Reclamation, 2013), which were chosen for the quality of their simulations of past drought variability in the region, as measured by PDSI. The simulations project that the Dallas area will be more prone to drought events—especially during the second half of the 21st century. This result is consistent with those of the region-wide simulations (Section 2.4). The DHSVM was then driven by each GCM's most severe drought from each of the two periods (2000-2049 and 2050-2099), using population projections to estimate water demand for the corresponding drought years. The simulations of reservoir storage show substantial impacts from both population growth and climate change (Fig. 5). During the first half-century most of the simulated future droughts have a shorter duration and a smaller impact on the supply reliability than the 1950s drought under the 2050 population projection. During the second half-century, each of the simulated future droughts leads to greater reservoir depletion than the 1950s drought, and some would be worse even without differences in population. For Dallas, which depends solely on surface water supply, this is a crucial water supply challenge. Further research to evaluate the water resilience of multi-reservoir systems (and alternative solutions, such as adjusting reservoir operation rules and/or constructing new reservoirs) is required to help address such challenges.

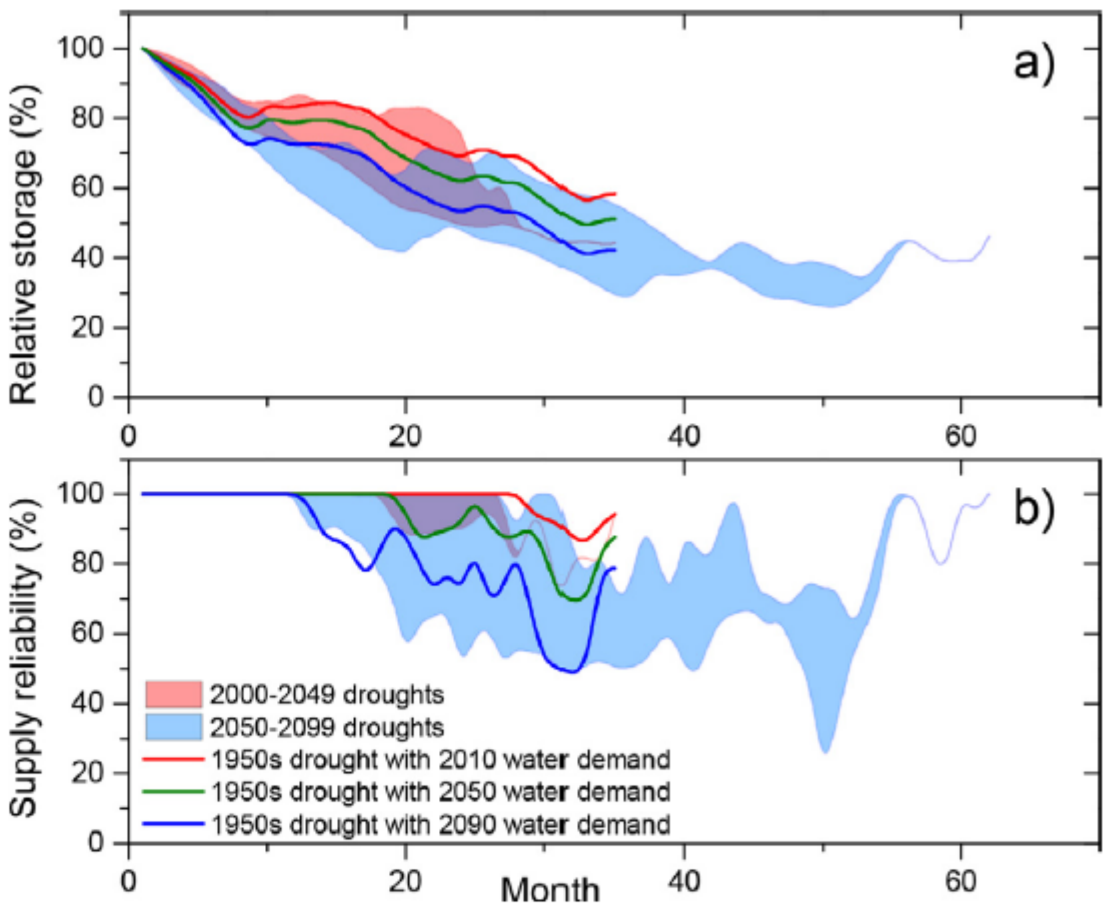


Figure 5: Responses of (a) relative storage and (b) water supply reliability to simulated CMIP5 hypothetical future drought events (with the corresponding water demand) and the 1950s drought (with the 2010, 2050, and 2090 water demand). Storage and water supply are the summation of 7 reservoirs in the Dallas-Fort Worth area. From Zhao et al. (2018), copyright Elsevier (2018).

Although not the subject of this paper, the impacts of climate change on reservoir operators go well beyond changes in water supply. For example, historic and projected increases in heavy rain events may alter the safety margins of existing dams and require retrofitting or reduced conservation pool size (Mallakpour et al., 2019).

3.3 Groundwater resilience

The Texas Water Development Board recognizes nine major aquifers and 22 minor aquifers in the state. Major aquifers are highly productive over large areas, whereas minor aquifers are either highly productive over a small area or moderately productive over a large area (George et al., 2011). These aquifers range from unconsolidated sands and gravels, to sandstones, to karst limestones. In general, the eastern half of the state has artesian aquifers while the western half of the state has unconsolidated and/or unconfined (non-artesian) aquifers.

Groundwater is connected to hydrologic systems through recharge, cross-formational flow to and from other groundwater systems, and natural discharge to seeps and springs. Recharge rates are directly tied to the volume, timing, and intensity of precipitation, but are also affected by soil types and soil profiles, vegetation, temperature, and the underlying geologic units between soil and the water table. Groundwater is most directly connected to human systems through extraction from wells. Longer-term human influences on groundwater include surface-water management, managed aquifer storage (using aquifers to store water from other sources), and human influence on climate.

Humans may also impact recharge through land use. For example, recharge rates have been observed to be higher in fallow fields than in actively cropped fields (Scanlon et al., 2007; Chen et al., 2018). In urbanized landscapes, where increased impervious cover ought to reduce infiltration and recharge, landscape irrigation and leaking water and wastewater infrastructure commonly result in a net increase in recharge (Sharp et al., 2003; Christian et al., 2011). The impacts of land-use on recharge may rival those of climate change, and the impact of these two factors may be synergistic.

Because deep, infiltrating water must flow from below the root zone to the water table, there is often a delay between changes in surface conditions and changes in recharge that can range from nearly instantaneous in some karst settings (Wong et al., 2012) to hundreds and even thousands of years (McMahon et al., 2011). Furthermore, due to the variability in recharge rates across an aquifer, water entering an aquifer today may consist of rainwater that fell decades to centuries ago during a range of climatic conditions. In this way, many groundwater systems are somewhat buffered against recent changes in climate.

Groundwater pumping ties directly to water demand, which in turn can depend on population, land use, economics, water use efficiency, climate, and weather. Drier and hotter conditions result in greater water demands for agricultural and urban irrigation as well as steam-electric power (driven by higher cooling needs). Groundwater pumping may reduce seeps and springs, thus affecting surface-water resources. Deleterious climate effects on surface-water resources may increase reliance on groundwater, thus further impacting groundwater resources and surface-water/groundwater interaction. Aquifer yield is also affected by groundwater management, which in turn may also be impacted by climatic changes, especially if those aquifers are being managed sustainably (Gleeson et al., 2011).

3.4 Quantifying future climate change effects on groundwater

Climate change can affect groundwater recharge by altering temperature, evaporation, rainfall amounts, intensity, and runoff. Impacts will vary depending on the characteristics of the aquifer and the landscape; Mace and Wade (2008) concluded that key factors include how quickly an aquifer recharges, the geologic setting, and land and water use. They noted that groundwater resources with high recharge rates, such as karst aquifers like the Edwards (Balcones Fault Zone) Aquifer, and highly permeable clastic aquifers like the Lipan Aquifer, are more susceptible to shorter-term changes in climate, whereas others with much slower recharge rates would still be affected, but would not show effects for decades if not centuries. They also noted that artesian groundwater resources in clastic aquifers—such as the Trinity Aquifer north of the Colorado River, the Carrizo-Wilcox Aquifer, and the Gulf Coast Aquifer—are unlikely to be affected by climate change as long as the rate of flow of water moving into the artesian zone (effective recharge) remains less than the total recharge rate. For Texas aquifers in general, though, one projection by Yoon et al. (2018) shows a general decline in groundwater recharge rates.

The Edwards (Balcones Fault Zone) aquifer is one of the most vulnerable aquifers to climate-change impacts in the U.S., because of its shallow depth and high karst permeability that make for rapid surface-subsurface connections (Loáiciga et al., 1996, 2000; Wong et al., 2012; Kloesel et al., 2018). Chen et al. (2001) investigated the possible effects of climate change on the Edwards Aquifer and projected a 1.5 to 3.5 percent increase in municipal demand, a 31.3 percent increase in agricultural irrigation demand, and a 20 to 30 percent decrease in recharge by 2090. These changes would reduce flow at Comal Springs, the largest spring system in the U.S. Southwest, by 10%-16% by 2030 and 20%-24% by 2090 and produce regional welfare losses of \$2.2–\$6.8M per year. Avoiding stress to endangered species by preventing flows at Comal Springs from going lower than 3 m^3 per second would require reducing the maximum amount of pumping in the San Antonio Segment of the Edwards (Balcones Fault Zone) aquifer from 608,000 m^3 per day to 473,000 m^3 per day (Mace and Wade, 2008). Mace and Wade (2008) argued that sea-level rise will not significantly affect groundwater resources in the Gulf Coast

Aquifer over the next century because most groundwater is extracted from deeper parts of the aquifer that have confining layers between them and the land surface/gulf. Uddameri et al. (2014) also found that regional scale sea-level rise over the Gulf Coast Aquifer would have limited impact on salt-water intrusion due to the flux of freshwater through the aquifer, at least in the Corpus Christi area, with withdrawal rates being a key factor in limiting or exacerbating such impacts.

It is clear that additional research is needed for specific aquifers to constrain the residence time of water moving from the land surface to the water table and how drought will affect freshwater flux. Greater priority should be placed on the more responsive aquifers that will exhibit climate change impacts sooner. These include the Blaine, Bone Spring-Victorio Peak, Capitan Reef Complex, Edwards (Balcones Fault Zone), Edwards-Trinity (Plateau), Ellenburger-San Saba, Hueco-Mesilla Bolsons, Igneous, Lipan, Marathon, Marble Falls, Seymour, and Trinity (south of the Colorado River) aquifers. Rainfall-runoff relationships under a warming climate should also be assessed for aquifers such as the Edwards (Balcones Fault Zone) Aquifer where a contributing zone funnels runoff to recharge features.

3.5 Adapting groundwater management to a changing climate

Groundwater in Texas is either managed by groundwater conservation districts or by rights holders withdrawing water. Groundwater conservation districts were founded to work collectively over a groundwater management area, such as a portion of a major aquifer, to establish a "desired future condition" (e.g., future water levels in that portion of an aquifer). This provides goals for managing groundwater resources in the district's area. The districts then pass and enforce rules to achieve that condition, through spacing of and restrictions on pumping. The Texas Water Development Board estimates how much can be pumped to achieve the desired future condition, a number called the modeled available groundwater. In areas without groundwater conservation districts, landowners can pump as much as they want, as long as water is not extracted for the purpose of harming other aquifer users and doesn't cause land subsidence.

Adapting groundwater management to climate change depends on how climate change impacts a particular aquifer. Changes in groundwater demand may be the most important climate-induced change for aquifers with very low recharge rates. In these cases, the modeled available groundwater would not change: pumping is pumping, regardless of what affects it. However, unanticipated increased demand by existing water users may create political stress.

In aquifers where climate change induced impacts to recharge become apparent over the next few decades, the modeled available groundwater may need to be re-evaluated. Desired future conditions are established for approximately 50 years into the future, a time horizon long enough for systematic changes to climate to impact groundwater in many Texas aquifers. Groundwater conservation districts can consider the effects of climate change, including using as a worst-case scenario a drought longer and more severe than that of the 1950's, when developing desired future conditions if they so choose, although they have not yet done so.

There are probably several reasons groundwater conservation districts do not consider climate change. One reason is that the establishment of desired future conditions as defined by state law does not require the consideration of climate change. Another reason is that climate change has become a political issue, and almost all of the districts regulate rural areas, which tend to be more politically conservative than urban areas. Ideally, a desired future condition is independent of the climate; however, many districts optimize their desired future condition to existing and planned pumping. By not considering the effects of climate change on recharge and groundwater demands, these districts may find their desired future conditions more restrictive than they anticipated.

Groundwater systems can be used conjunctively with other sources of water to expand water resources. For example, surface water can be treated, injected, and stored in an appropriate aquifer for later use without evaporative losses. In rapidly recharging aquifers, recharge can be enhanced by directing excess surface water or treated wastewater into infiltration basins or recharge features. There may be unintended consequences that need to be weighed, however, such as less water for downstream users and the environment, and a reduction in water quality.

4. Alignment of climate science research with stakeholder needs

The preceding sections discuss what is known about observed and future climate trends and their impacts on Texas water resources. This section discusses the knowledge that water users, managers, and planners need in order to appropriately incorporate climate change information into their operations. It is organized around the perspectives of four sets of stakeholders – agricultural producers, large surface water suppliers, small groundwater planning districts, and regional water planning districts. These are designed as representative examples, and not intended to be comprehensive. Other stakeholders and sectors in Texas, such as power generation, oil and gas exploration, wildlife management, and manufacturing, have future water information needs that are similarly specific and difficult to satisfy with generic climate change information. For example, major industrial water users need to ensure the reliability of their water supply with future climate change, and climate change information alone doesn't elucidate how suppliers will adapt capacity, how other users will adjust water demands, or how likely a particular supply will drop below a particular level (e.g., Reddy et al. 2015).

In each case, actionable, incompatible, and unavailable climate science information is identified from the perspective of the stakeholder. *Actionable information* is information that can be directly or easily used in decision-making. *Incompatible information* is information that is available and has the potential to aid decision-making but cannot be used without additional, and often substantial, expert input. These are similar to the usable and useful information categories of Lemos et al. (2012). *Unavailable information* is information that is necessary for full consideration of climate change but which is not available and may not be obtainable under the present state of science and technology.

<u>Case 1: Agricultural producers</u>

Climate information is most directly relevant to agricultural producers in the form of probabilistic seasonal outlooks. Decisions such as the appropriate crops to plant (and when to plant them) and herd stocking sizes depend on expectations for the coming seasons.

Texas' significant inter-annual weather and climate variability demonstrates the need for actionable seasonal forecasts. Various specific decisions with particular lead times are made during certain times of the year (Mase and Prokopy 2014; Klemm and McPherson 2018). Particularly valuable for agricultural producers would be actionable forecast guidance that is available in fall and winter for conditions in the following warm season. Unfortunately, the influence of predictable oceanic features such as El Niño – Southern Oscillation is relatively low during the warm season, limiting the present-day utility of such forecasts. Even during more predictable seasons, forecasts rarely rise above the level of accuracy required for adoption by risk-averse farmers (Garbrecht et al. 2010, Kusunose and Mahmood 2016

Information regarding the probabilities of seasonal-mean conditions are less relevant than predictions of the chance of extreme events such as droughts and blizzards. The severity threshold of extreme events can be both crop and location specific, requiring a method for producers to translate seasonal forecasts into measures of comparative risk. Producers, however, will not necessarily be able to translate their agricultural threshold event parameters into meteorological terms. As seasonal forecasts become more skillful, there is a growing opportunity for the private sector to translate those forecasts into actionable information for producers, such as the likelihood that rainfall over the next three weeks will ruin a mature cotton crop (Klemm and McPherson 2017).

Climate change information is relevant on a year to year basis because producers often rely on experience with past climatological events when planning, such as selecting which crops to plant. In that context, it is important for producers to know whether unusual events in the recent past represent an anomaly or the realization of a long-term trend. The answer will need to be specific to the type of events that have the greatest impact on local operations, such as available soil moisture during planting season or precipitation during the growing season. Since producers are aware of past impactful climate events, this guidance can usefully be framed in the context of past trends, and the extent to which past events and their frequency are representative of future events and their frequency. For example, the observed impact of a past drought can be projected for a future event of similar magnitude and duration.

Climate change information can inform longer-term planning decisions such as which crops to grow, which breeds to invest in, when to buy or sell land, or even which type of operation to run. General guidance is available from projections of temperature, precipitation, and other such parameters (Awal et al. 2016; Modala et al. 2017), but the most valuable information would be location-specific projections of size and variability of crop yields, given projected changes in climate means and variability and confounding factors such as insects

(Steiner et al, 2017; Deutsch et al, 2018). Existing Texas projections for crop yields (Adikhari et al. 2016, Chen et al. 2019, Kothari et al. 2020) and irrigation requirements (Fares et al. 2017; Awal et al. 2018) typically consider only subset of important factors and adaptation responses, making interpretation by agriculture stakeholders challenging.

Case 2: Large surface water suppliers

Surface water suppliers typically make long-term infrastructure planning decisions based on a single deterministic target. The most common target is firm yield, which is the amount of water that can be reliably delivered during an extreme drought. In Texas, the extreme drought that is used for planning purposes is the "drought of record" as discussed above. Until recently, that drought was the drought of the 1950s. For some basins, however, such as the Lower Colorado River basin, the drought of the 2010s will be the new drought of record. Regardless of the specific impact of climate change on future droughts, future climate change will alter the relevance of the historical drought of record to future water supply reliability.

Suppose, for illustration, that the drought of record is known to be the worst in 100 years. In a stationary climate, a worse drought would have roughly a 2 in 5 chance of occurring within the standard planning horizon of 50 years. To maintain the same resiliency for planning purposes in a changing climate, a planner would need to know the firm yield during a drought with a 2 in 5 chance of occurring within the next fifty years given the changing climate. Since planning is done decade by decade, decadal estimates of firm yield during a drought with, say, a 1 in 10 chance of occurring within a given decade would be useful, as well as similar decadal projections beyond the 50-year window.

There are two challenges to providing those estimates. The first involves the meaning of the probabilities themselves, and the second involves the estimation of future firm yield.

Individual probability estimates from historical data reflect the partially random nature of actual weather and climate events. Even given the same historical data, different techniques for estimating probabilities can produce different values. This source of error is called structural uncertainty (Ajami et al., 2007). Structural uncertainty does not exist for the drought of record, since it is an actual event. Indeed, the current planning process is directed toward a single target without explicit uncertainty, so any incorporation of probabilistic information would represent a fundamental change in the planning approach. There is structural uncertainty, for example, in estimating the recurrence frequency, with the estimate given above being one crude way of doing so.

The future climate is not known, so - as discussed previously - there is additional uncertainty inherent in future firm yield projections. These uncertainties arise from future carbon emission scenarios and other climate drivers, different possible magnitudes and rates of response of the global climate system to these drivers, and different possible consequences to particular water suppliers from a given change in global climate. Should these uncertainties be folded into decadal drought severity probabilities, or should a single "best guess" scenario, climate response, and local impact estimate be used to inform future water planning? Neither the probability distribution of actual scenario uncertainty nor the single "best guess" can be fully quantified, and the IPCC AR5 refrained from providing sufficient quantitative information on expert judgment of climate sensitivity to fully characterize the probabilities or even specify a "best guess" (IPCC, 2013). Confronted with these uncertainties, some water suppliers, such as Denver Water, have found it appropriate to plan for multiple scenarios rather than a specific climate projection (NASEM 2019). Past state water plans in Texas considered multiple scenarios for population and water demand projections, but not for uncertainty in water supplies (TWDB 1984, 1990, 1997); water plans since 1997 have been based on single scenarios.

Obtaining any estimate of future yield is challenging, let alone developing a probability distribution that includes structural uncertainties. The information needed are time-dependent inputs to models such as the Water Availability Model (WAM) (Wurbs, 2005) that were not originally designed for a nonstationary climate. Appropriate inputs are unavailable from global climate models, so watershed-specific downscaling or other methods of generating detailed future scenarios are needed. Statistical downscaling techniques assume that the relationship between larger-scale weather or climate conditions and precipitation and runoff remain constant, but there is little guidance on the reliability of those assumptions for water supply purposes. In a changing climate, the aspects of precipitation that will possibly change are its total amount, seasonality, temporal and spatial granularity, and intensity. Other environmental factors related to the water cycle will also change, such as temperature-driven evaporation rates, the response in soil moisture to changes in precipitation, atmospheric carbon dioxide, and the migration and water use efficiency of plant species. Projections need to either incorporate all such factors or demonstrate that excluded factors are unimportant. So, for water suppliers, not only is the task of developing WAM inputs from climate projections difficult, but so is the task of identifying the appropriate (set of) projections and including them in a process that assumes a single event. Only the largest suppliers have the capacity to undertake such an effort on their own and to deviate from standard single-scenario planning.

Case 3: Small groundwater management districts

As discussed above, there can be a lag of years to decades and more in the response of groundwater to climate impacts, depending on the characteristics of the aquifer and the region.

Instead, the impact of climate on demand or human response may be the most important factor short-term. Thus, quantifying climate change impacts on water demand involves not just the types of obstacles identified on the supply side in Case 2, but also the challenge of predicting the response of human actors to the physical impacts of climate change. For example, how willingly and rapidly will people move to more water efficient practices, such as switching to less water-intensive crops or landscaping? Without addressing such questions, projections of change in evaporation and rainfall only produce a partial bound on the change in water demand.

A challenge shared by small groundwater districts and small surface water suppliers is the relative lack of in-house technical expertise on the science of climate change. Without such trusted expertise, managers must formulate their own opinions regarding climate change or be more likely to reflect the opinions of their customers. The value of qualitative climate change information, such as projections of temperature, precipitation, and drought severity, depends in large measure on whether a water manager would be able or even willing to use them. Given the existence of skepticism regarding climate change, adoption of climate change information can be limited by the extent to which a non-expert can recognize that the projections are well-founded and unbiased. Satisfying this requirement involves both perception and reality; the mere existence and availability of well-founded and unbiased projections are insufficient.

There are various ways that well-founded and unbiased projections can come to be perceived as such. One is to relate the projections to historical information. If it can be demonstrated, through analysis of observations or through modeling, that the future projected conditions predominantly represent a continuation of an ongoing trend, those projections become more plausible. Secondly, it is important to remember that groundwater managers, like surface water suppliers and agricultural producers, need both short and long-term climate information. If seasonal forecasts become more reliable and can be tailored to the key needs of water managers, confidence may build in the ability to provide reliable (or at least unbiased) longer-term projections. One shortcoming of this approach is that, until recently, the techniques for climate change projections and seasonal forecasts had very little overlap, so credibility on one endeavor did not imply credibility in the other. That gap is closing with the growing use of coupled climate model outputs as resources for seasonal forecasters (Slater et al., 2016).

Case 4: Regional water planning groups

The state planning process starts with regional plans developed for 16 regional water planning areas that cover the state. The Regional Water Planning Groups charged with planning for these areas must deal with all the issues discussed in the other three cases, except that they are usually not involved in short-term operation decisions. In addition, they must deal with water supplies as a collection of semi-autonomous, interdependent systems. Climate impacts in one portion of one system can propagate through the other systems in unexpected ways. One example is the effect of rising temperatures driving increased energy demand since Texas uses slightly more energy to cool than to heat (Zhou et al., 2014). Rising energy demand means increased need for cooling water for conventional power plants, and this, in turn, can lead to conflicts between power suppliers and other water users. Another set of issues on the supply side is the effect of climate change on renewable power generation. How will solar photovoltaic cell efficiency be affected by changes in cloud cover? How will long-term wind speed changes affect the viability, efficiency, and optimal spatial distribution of wind turbines?

Given the lack of system-specific, quantitative climate change information, a reasonable approach for a water planning area would be to develop multiple water supply sources that respond to droughts and climate change in different ways, or to develop water supply sources that are insensitive to climate change. One difficulty with that approach is that there is often limited capacity to develop new supply sources. Another difficulty to building resiliency of water supplies is that resiliency implies sources greater than any immediate need, and it can be difficult to obtain permits for projects that apparently are not serving an immediate need.

With regional water planning groups serving a diverse range of stakeholders, challenges of incorporating climate change information are magnified. With no established framework for incorporating climate change information, such groups must have the technical expertise and institutional capacity to develop their own frameworks. They also need the ability to convince their stakeholders not only that considering climate change is appropriate but that their chosen approach is the proper way to do so.

5. Researcher-Stakeholder Alignment Effort: Austin, Texas

The City of Austin's water utility, Austin Water, serves over 1 million customers. The 2011 statewide drought motivated the city to prepare a 100-year integrated water resources plan that considers climate change, known as Water Forward (Austin Water, 2018). Austin Water developed this plan with support from a task force comprised of City-Council-appointed stakeholders from the public and ex officio members representing various city departments. Austin's City Council adopted the Water Forward final plan in November 2018. The plan anticipates five-year updates to address adaptive management. Two of us were involved in plan development, one with the City of Austin (M.F.G.) and one as a source of climate change information (R.H.).

GCMs formed the basis of Water Forward's consideration of climate change. A total of 20 GCMs were run through the year 2100 using the expected warming effects of different future scenarios (Hayhoe et al., 2016). The outputs of the GCMs were converted into local estimates of future precipitation and temperature at pertinent stream gages and reservoir sites across the Colorado River Basin, in which Austin is located. These local weather variables were used to derive sets of stochastic future streamflow conditions based on the historical relationships of streamflow and weather. The 20 GCM-derived streamflow sequences at each stream gage were used as an ensemble forecast to describe a range of possible future hydrologic conditions and to adjust the historical record to create future streamflow sequences that range from 1) having an equal chance of occurrence as the drought of record to 2) up to three times rarer than the drought of record, both in present and future climate. This provided a set of possible design events in a context understandable to a non-expert. With an adjusted historical record that reflects possible future hydrology, a basin-wide water availability model was used to simulate streamflow and reservoir storage, including water availability for the City.

At the outset, hydrologic modelers and planners outlined the needs for basin-wide streamflow and weather variables at specific locations that coincided with future planning horizons. The basin-wide locations were consistent with historical streamflow and weather inputs used in the water availability modeling tool used for Water Forward. The climate scientists were able to derive the streamflow and weather variables at the local level from the GCM output. Therefore, the information provided by the climate scientists had a high degree of utility in driving local and basin scale water availability modeling. GCM-derived streamflow and weather was readily converted into a format that could be used as input for local and basin-wide simulations.

The climate change information was generally greeted with acceptance by the stakeholders and public. Several factors may have contributed to the positive view, including clear communication in a layperson's terms from the climate scientist to the stakeholders regarding the status of climate science and the need to plan for future conditions, the unprecedented drought conditions in the early 2010s, and community understanding and acceptance of the science. The clear communication and understanding, in turn, were facilitated by having frequent meetings and communications between the climate scientists and City staff, rather than a scope of work handed off to the climate scientists and a deliverable produced at the end of the contract period. The process helped raise the level of understanding and confidence for the non-climate scientists who were involved in creating the plan. The City staff were better equipped to communicate the climate scientists' work products to their management as well as stakeholders. The stakeholders were also able to benefit from several meetings with the climate scientist present and available to answer questions. The sources of uncertainty in generating climate change information were acknowledged in the planning process including the influence of natural variability, human choices, scientific uncertainty, and uncertainty in translating regional-scale changes in climate into local-scale changes in hydrology. While there were no formal or quantitative measures of uncertainty cited, this did not form an obstacle for proceeding with considering climate change as a fundamental component of Water Forward.

6. Paths Forward

We have examined some of the pressing challenges and near-term opportunities for incorporating climate change projections into improved water resource management strategies. Considerable information on historical and future climate exists, but information, knowledge, and resource gaps preclude direct use of most of this information for water planning purposes, even in a relatively resource-rich location such as Texas. Each location will have its own unique challenges, but identifying those challenges requires a comprehensive examination of stakeholder needs and circumstances. Many challenges exist that are not directly discussed here, such as lack of technical capacity, the lack of established techniques of incorporating climate change information, and challenges associated with obtaining buy-in from diverse customers and political leaders.

By examining informational needs through the lens of four separate stakeholder groups, we identify key areas of research for Texas that will synergistically inform scientists and stakeholders:

- A coordinated E-W study of Late-Pleistocene to Holocene-age moisture proxies to reconstruct past shifts in the position of the '100^{th} Meridian' wet-dry transition would yield valuable insight into teleconnections between global climate change, including during abrupt warming events, and local hydrologic extremes that will impact Texas' rapidly growing urban corridors.
- Bridging the gap between generating downscaled GCM precipitation data and accurately projecting local streamflow and soil moisture is a significant technical challenge that requires collaboration across a range of disciplines, as demonstrated by Austin's Water Forward. Solving this challenge allows engineers and hydrologists to readily adapt the WAM used in Texas to represent future conditions over time scales relevant to stakeholder needs.
- Not planning for droughts worse than the drought of record is a glaring and long-standing insufficiency in the current state water planning process (Banner et al., 2010), especially since some areas of the state recently experienced a new drought of record. Addressing the question "How much worse should we plan for?" is an opportunity for planners and scientists to collaborate and learn from each other.

- Direct linkages to data, information sources, and decision-making frameworks, with transparent communication of calculational and structural uncertainties of high-resolution climate projections and associated hydrologic projections, are critical for maximizing the extent to which non-experts recognize that the projections are well-founded and unbiased, and thus feel confident making decisions that increase resilience for Texas.

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Supporting Information for

Unprecedented drought challenges for Texas water resources in a changing climate: what do researchers and stakeholders need to know?

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Contents of this file

Introduction

This document provides details and supplementary figures for the comparison of past and future drought conditions presented in Section 2.4.

Text S1.

For each region (west and east), drought reconstructed from the North American Drought Atlas (NADA) was compared to drought calculated from climate parameter output (e.g., temperature, precipitation, humidity) simulated by climate models using historical estimates of natural and anthropogenic climate forcings from 1850-2005 and the Representative Concentration Pathway (RCP) 8.5 (a high-end business-as-usual scenario) from 2006-2099 (models listed in Table S1). Three indicators of drought were calculated for the months of June through August – PDSI, soil moisture integrated from the surface to 30 cm (SM-30cm), and soil moisture integrated from the surface to 2-3 m (SM-2m) – and standardized to the same mean and variance as PDSI to allow direct comparison. In this way, analyses of soil moisture quantities that incorporate processes not included in the PDSI calculation (e.g., snow, soil freezing, CO_2 fertilization, vegetation dynamics) can be accounted for in the CMIP5 drought projections. PDSI and soil moisture from the models and NADA, respectively, were re-centered to a mean of zero from 1901-2000, so that numerical values represent changes (wetter or drier) relative to the 20th century baseline average. Results are shown for individual models and for the collective multi-model ensemble (MME).

Over the historical period (1850-2005), PDSI is strongly correlated in most models with the standardized shallow (SM-30cm) and deep (SM-2m) soil moisture indicators (Fig. S2), even though PDSI represents a quasi-independent calculation of soil moisture balance. This indicates that, despite its simplicity, PDSI provides a reasonable approximation of soil moisture variability in these models, and that this approach is appropriate for assessing drought variability. Correlations are similar when calculated over the RCP 8.5 interval (2006-2099; not shown), although differences in the formulations and sensitivities of the indicators often result in differences in long term trends and responses to warming.

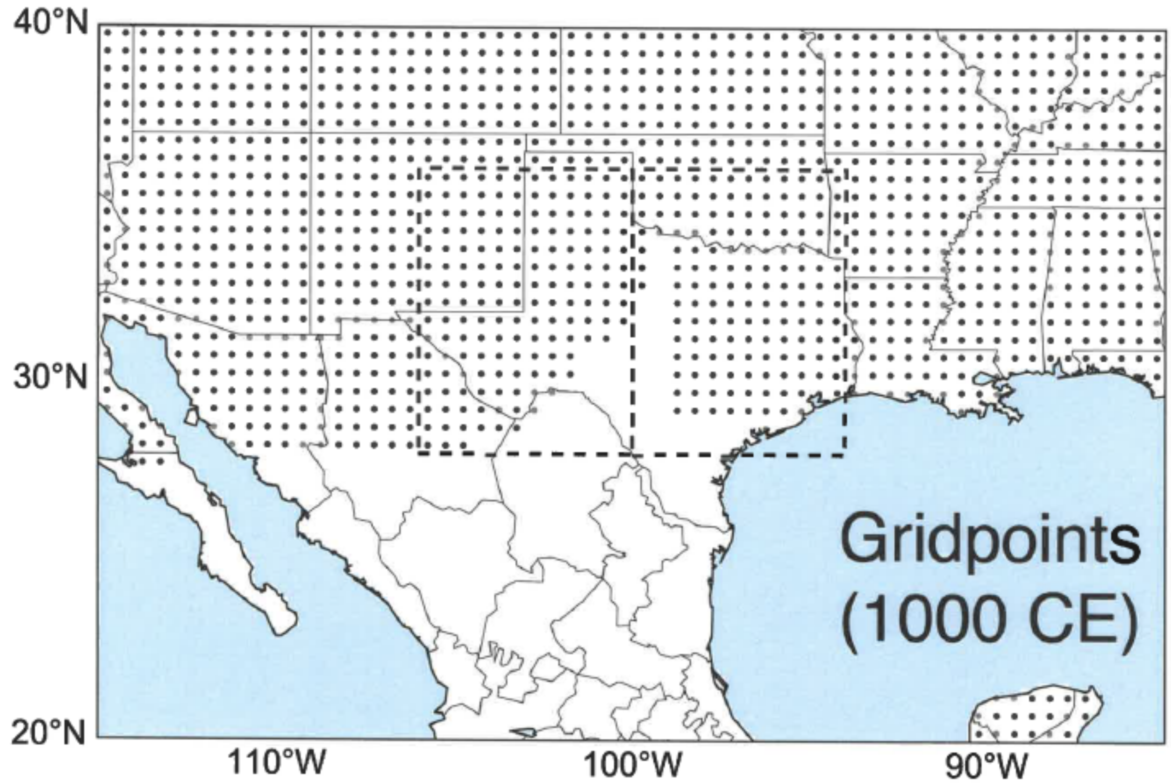

Figure S1. Gridpoints used to generate climate projections for East and West Texas, as outlined in dashed boxes. The two boxes are separated by the 100th meridian (the nominal wet-dry line).

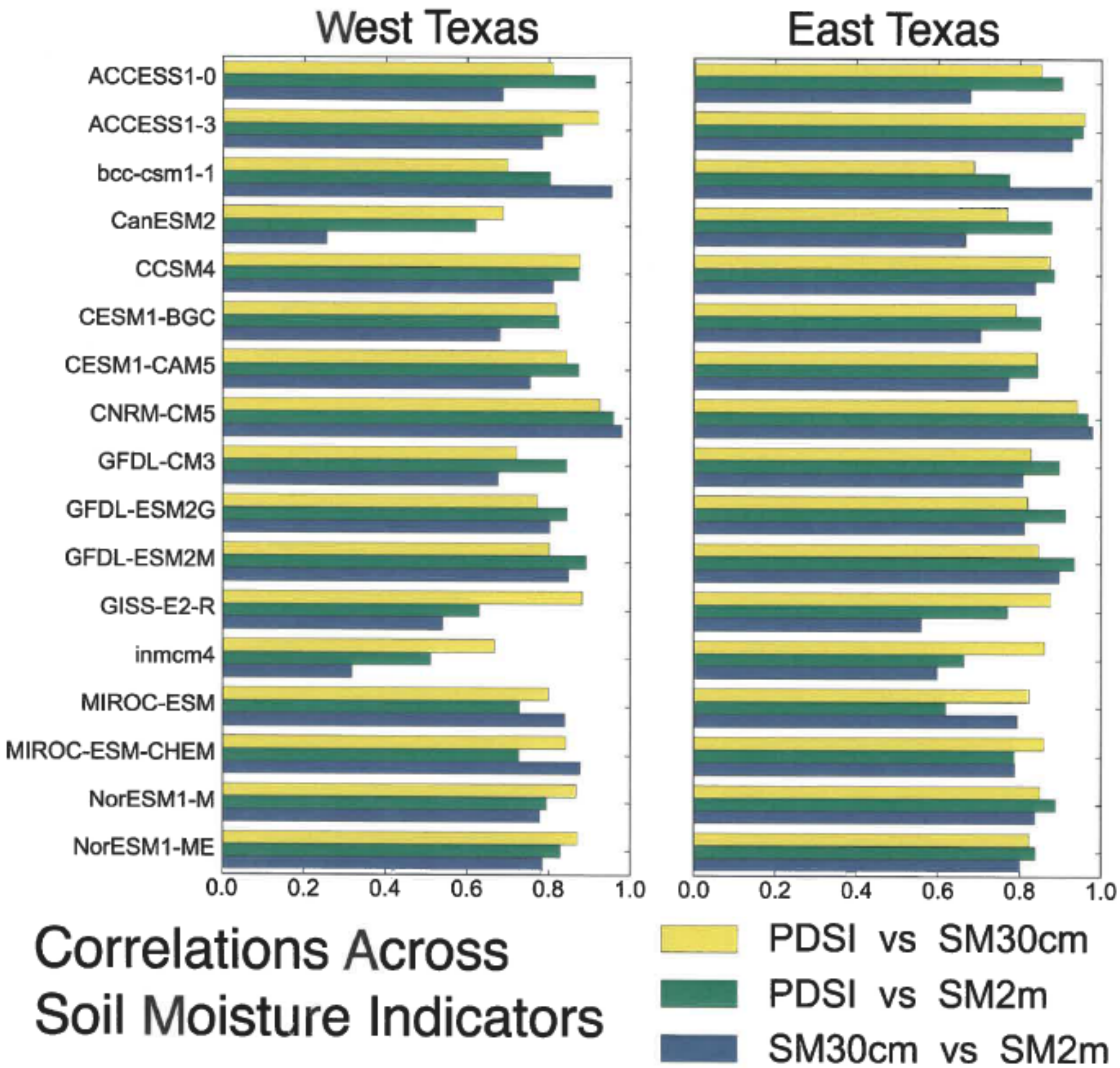

Figure S2. Correlations between model-simulated indicators of soil water availability for west (left panel) and east (right panel) Texas for the years 1850-2005.

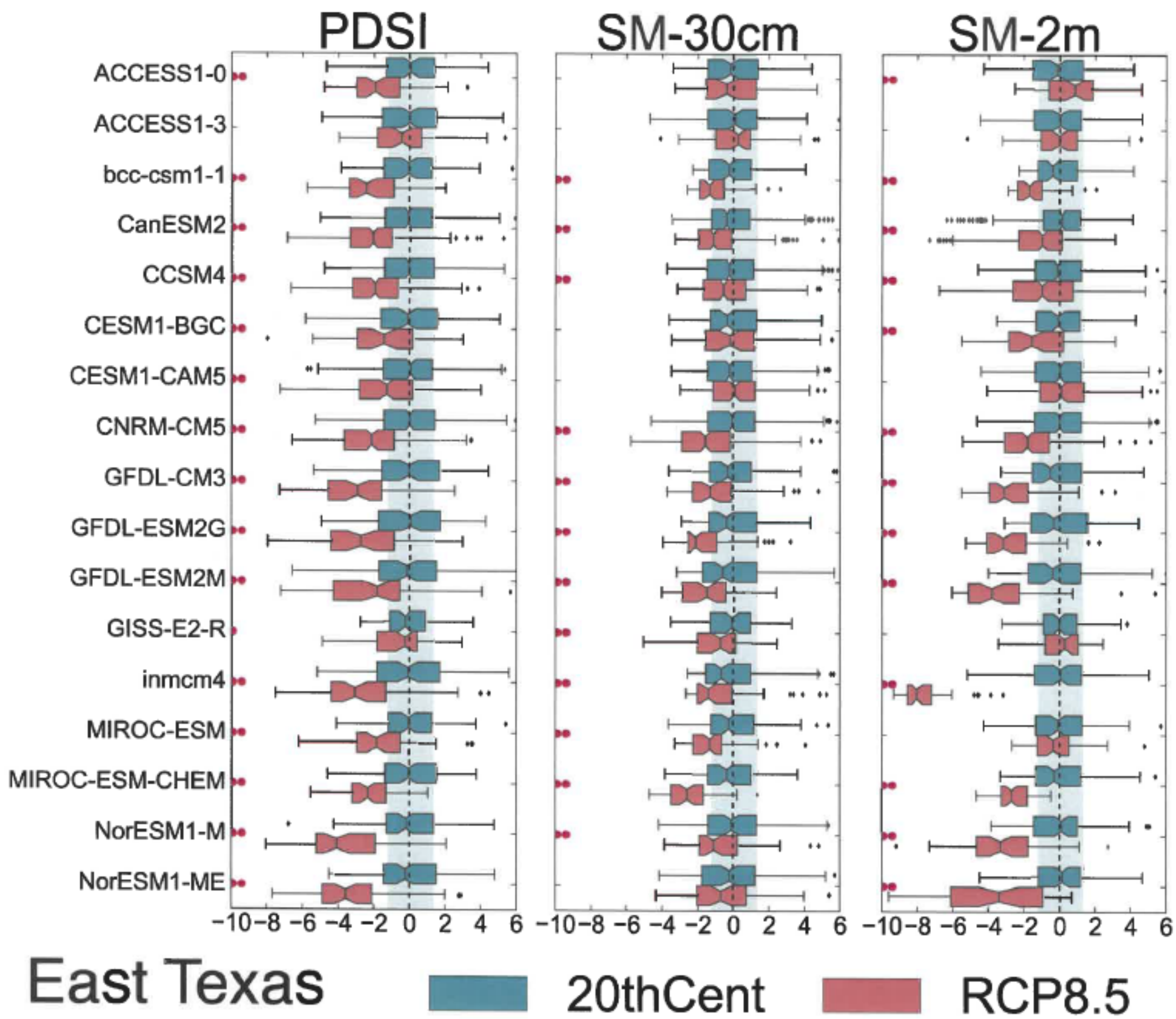

Figure S3. Box plots generated for 17 GCMs across three soil moisture indicators over the 20th century (blue) and projected through the 21st century under the RCP8.5 emissions scenario in east Texas. Most models project significant drying in the latter half of the 21st century.

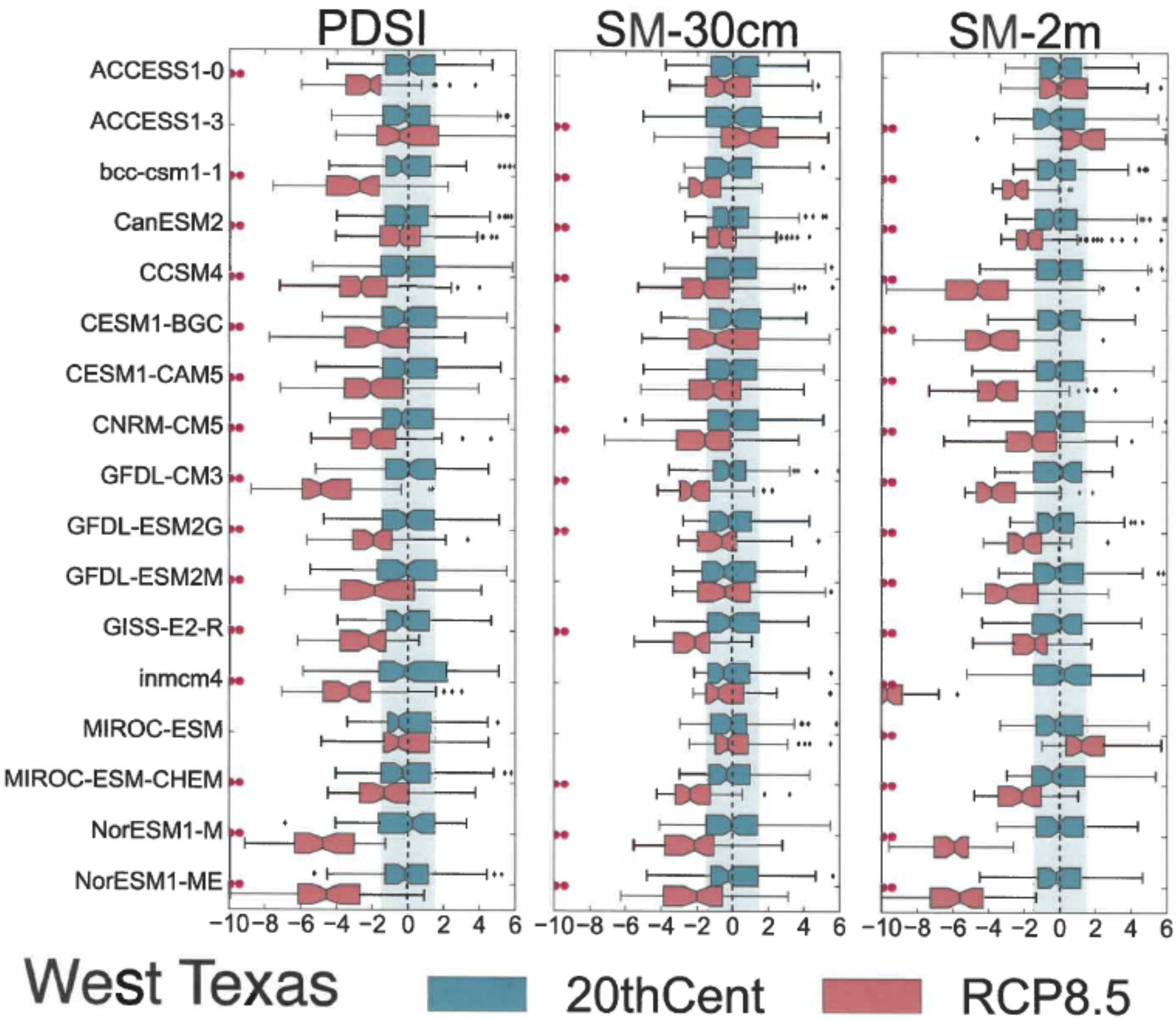

Figure S4. Box plots generated for 17 GCMs across three soil moisture indicators over the 20th century (blue) and projected through the 21st century under the RCP8.5 emissions scenario in west Texas. Most models project significant drying in the latter half of the 21st century.

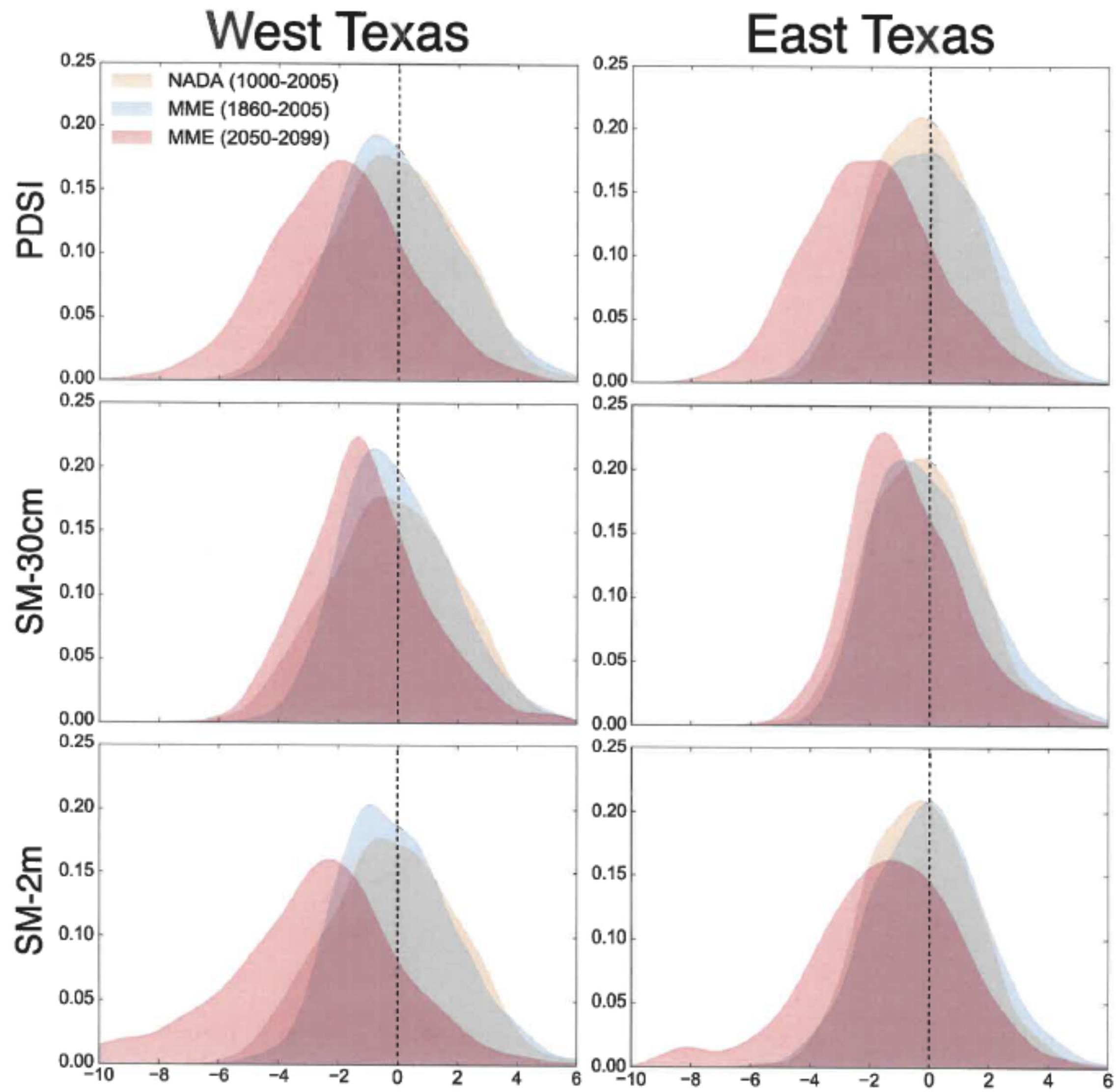

Figure S5. Probability distributions for three soil moisture indicators in west (left panel) and east (right panel) Texas in paleoclimate data (NADA, yellow) and in the multi-model ensemble (historic simulations in blue and RCP8.5 simulations for the late 21st century in red. Late 21st century shifts in moisture availability are observed across all three indicators.

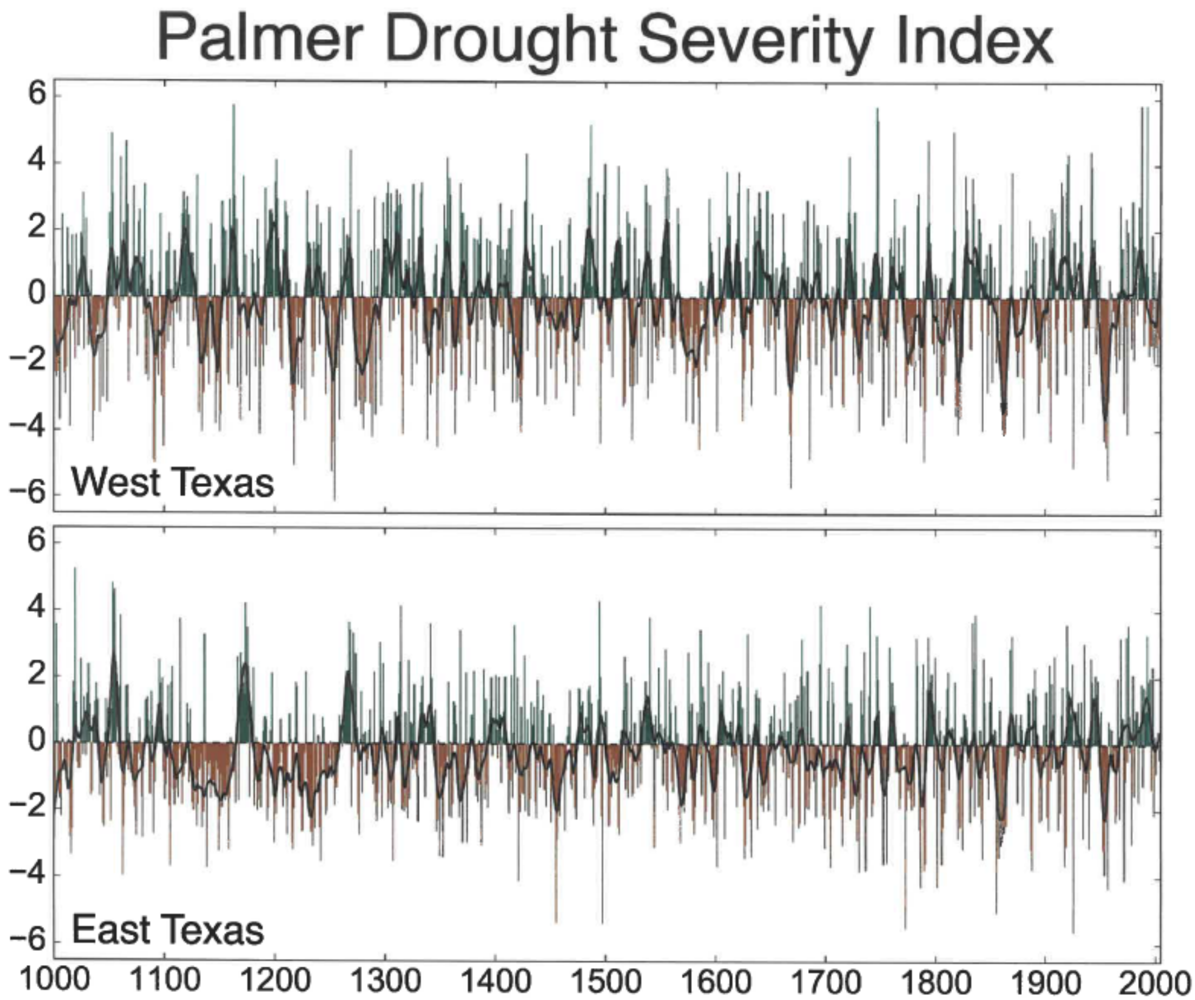

Figure S6. Annual and smoothed June-August PDSI values for West and East Texas according to the North American Drought Atlas. Compare with projections of future climate (Figs. 3 and 4).

Model	Modeling Center/Group	# of Ens. Members
ACCESS1.0	CSIRO-BOM[a]	1
ACCESS1.3	CSIRO-BOM[a]	1
BCC-CSM1.1	BCC[b]	1
CanESM2	CCCMA[c]	5
CCSM4	NCAR[d]	6
CESM1-BGC	NSF-DOE-NCAR[e]	1
CESM1-CAM5	NSF-DOE-NCAR[e]	3
CNRM-CM5	CNRM-CERFACS[f]	4
GFDL-CM3	NOAA GFDL[g]	1
GFDL-ESM2G	NOAA GFDL[g]	1
GFDL-ESM2M	NOAA GFDL[g]	1
GISS-E2-R	NASA GISS[h]	1
INMCM4.0	INM[i]	1
MIROC-ESM	MIROC[j]	1
MIROC-ESM-CHEM	MIROC[j]	1
NorESM1-M	NCC[k]	1
NorESM1-ME	NCC[k]	1

[a]Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia
[b]Beijing Climate Center, China Meteorological Administration
[c]Canadian Centre for Climate Modelling and Analysis
[d]National Center for Atmospheric Research
[e]Community Earth System Model Contributors
[f]Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation Avancée en Calcul Scientifique
[g]NOAA Geophysical Fluid Dynamics Laboratory
[h]NASA Goddard Institute for Space Studies
[i]Institute for Numerical Mathematics
[j]Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
[k]Norwegian Climate Centre

Table S1. Continuous model ensembles from the CMIP5 experiments (1850–2099, historical+RCP8.5 scenario) used in this analysis, including the modeling center or group that supplied the output and the number of ensemble members. All model diagnostics were retrieved from the Earth System Grid Federation (ESGF) CMIP5 database (**https://esgf-node.llnl.gov/projects/cmip5/**)