Title
Amplified climate warming under drought conditions in observations and model simulations

Author
Chiang, Felicia

Publication Date
2017

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA,
IRVINE

Amplified climate warming under drought conditions
in observations and model simulations

THESIS

submitted in partial satisfaction of the requirements
for the degree of

MASTER OF SCIENCE

in Civil Engineering

by

Felicia Chiang

Thesis Committee:
Associate Professor Amir AghaKouchak, Chair
Professor Kuo-lin Hsu
Associate Professor Steven J. Davis

2017

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ACKNOWLEDGMENTS

I would like to express my gratitude to my committee chair, Professor Amir AghaKouchak, for his direction and counsel during the course of the study. I would also like to thank my committee members, Professor Kuo-lin Hsu and Professor Steven Davis, for sharing their knowledge and insight with me. I also want to acknowledge and thank Omid Mazdiyasni for his initial work and input in the study. This project was partially supported by the NOAA MAPP program.

I acknowledge the World Climate Research Programme's Working Group on Coupled Modeling, which is responsible for CMIP5, and thank the climate modeling groups (listed in the appendix of this thesis) for producing and making their model output available to the public. For CMIP, the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

ABSTRACT

Amplified climate warming under drought conditions
in observations and model simulations

By

Felicia Chiang

Master of Science in Civil Engineering

University of California, Irvine, 2017

Associate Professor Amir AghaKouchak, Chair

Global temperatures have risen 0.6 degrees Celsius in the 20th century and have been projected to rise an additional 1.0-3.7 degrees Celsius in the 21st century depending on the emissions scenario. Climate records also show that drought events have been occurring more frequently during high temperature anomalies. Previous studies show strong feedbacks between drought conditions and surface temperatures, which prompted the question of whether drought conditions are experiencing larger temperature increases in comparison to the average climate. The objective of this study was to investigate whether droughts have been warming faster than average climate conditions in the contiguous United States. Using gridded observations and climate models, we compared temperatures during different categories of drought severity on a monthly scale and mapped areas displaying an escalation of temperature with stricter definitions of drought. We observed a historical shift of warming temperatures during dry months in Southern and Eastern regions between the early and late halves of the 20th century. Future projections also showed a larger warming shift during dry months in the Southern US

between the 20th and 21st centuries. In the climate projections, the higher temperature shift was mostly attributed to the summer months. The summer associated temperature shift is rooted in preceding winter and spring precipitation, which influence the surface energy balance in regions with moderate climate. These mid-latitude temperature shifts associated with dry conditions are an important piece in understanding and deconstructing climate conditions in a rapidly changing environment.

INTRODUCTION

In the 20th century, global temperatures experienced an increase of 0.6 degrees Celsius [IPCC, 2007]. Based on a portfolio of emissions scenarios, temperatures have been projected to rise an additional 1.0-3.7 degrees Celsius in the 21st century [IPCC, 2013]. Recent warming conditions have contributed to the occurrence of dry periods since the mid-20th century by increasing the water holding capacity of the atmosphere [Dai, 2011; Dai, 2013]. 21st century climate change projections have also predicted declining soil moisture across the globe in every emissions scenario [Sheffield and Wood, 2008].

Many studies have highlighted the strong feedback effects between land surface and atmospheric conditions [Seneviratne et al., 2006; Fischer et al., 2007a]. Land surface moisture conditions influence local temperatures through the modulation of evaporation levels, which has been observed in the connection between summer heat waves and preceding precipitation conditions in Europe [Fischer et al., 2007a; Whan et al., 2015]. Fischer et al. [2007a] also noted that droughts can exercise remote influences on surrounding areas through advection and changing circulation patterns. In addition, regional climate model results suggest mutual feedbacks exist between soil moisture and continental circulation patterns [Fischer et al., 2007b]. Whan et al. [2015] found that the extreme temperatures of the 2003 European heatwave could have been higher with drier antecedent soil moisture levels. For our study, we examined shifts in temperatures occurring during dry months to further explore the feedbacks between surface moisture and temperature conditions. The objective of the study was to evaluate whether dry conditions experience an amplified rate of warming relative to the average climate.

CHAPTER I

Droughts and warm periods

Droughts have had severe urban, agricultural and ecological impacts historically and in recent years, directly and indirectly reducing water availability [Rosenzweig et al., 2011; Lake, 2011]. Warm periods have also impacted urban, agricultural, and economic sectors by stressing the health of vulnerable populations, food resources, and energy generation and transportation systems [McGregor, et al., 2007; Rosenzweig et al., 2011]. In addition to the individual effects of these climate events, occurrences of heat stress during times of water scarcity have produced compounding climatic effects [Mazdiyasni and AghaKouchak, 2015]. Dry surface conditions have been shown to intensify warm periods through changing the Bowen ratio between sensible and latent heat, which have produced environmental and social ramifications [Chang and Wallace, 1987]. Drawing from established interactions between drying and warming conditions, we studied whether temperatures during dry conditions will be changing under the context of climate change. Due to projections showing drought and high temperatures intensifying independently over the next century, the goal of the study was to understand whether temperatures are projected to experience different rates of intensification when coupled with drier than average conditions [IPCC, 2013].

Review of historical drying patterns

Evidence of stronger dry and wet events have previously been observed in tropical rainfall, in evapotranspiration from river basins in the United States, and in the expansion of drought areas in Asia and Africa [Huntington, 2006; Chou et al., 2009]. Although these studies have documented an intensification of the hydrologic cycle where the dry regions are becoming drier and the wet regions are becoming wetter, Greve et al. [2014] has shown that the simple theory of an intensified spatial pattern does not explain all of the observed changes occurring in water distribution around the world. To follow these studies, we explored whether more severe temperatures can also be associated with the 'dry gets drier, wet gets wetter' spatial pattern in observations and models. Precipitation has long been physically correlated with temperature, due to the effects of clouds and water on the surface energy balance [Livneh and Hoerling, 2016]. We explored this correlation further by studying if future warming or cooling trends will align with the dry or wet conditions that characterize each region.

Study objectives

Characterizing the changing effects of preceding rainfall conditions on temperature are important for interpreting future climate projections and improving model accuracy. We evaluated whether historical and climate model datasets have shown evidence of these changes in the conterminous United States. For our study, we researched the relationship drought severity has exhibited with temperature changes in gridded historical observations as well as in model simulations. We compared temperatures during different drought severities in two observed periods [1902-1951 and 1965-2014] and two modeled periods [1951-2000 and 2050-2099]. Drawing on the simple negative correlation between temperature and precipitation, we hypothesized that temperatures from drier months would show higher shifts between time periods than temperatures from the average climate in all regions of the United States. In addition, since many studies have documented the dry getting drier and wet getting wetter spatial pattern, we also predicted that regions with historically dry climate conditions would experience greater shifts in dry month temperatures.

CHAPTER II

Climate data

For our observations, we used monthly temperature and precipitation data available from the Climatic Research Unit, CRU TS3.23, which is a gridded time-series climate dataset [Harris et al., 2014]. The data coverage included all areas of the contiguous United States at a 0.5 degree resolution. We used the bias-corrected spatially disaggregated (BCSD) downscaled CMIP5 multi-model ensemble at a 0.125 degree resolution available from the US Bureau of Reclamation website [Maurer et al., 2007; Reclamation, 2014]. The BCSD method is a statistical downscaling method that uses the probability density functions of model output mapped onto observations and then spatially aggregates the results to the desired scale [Maurer and Hidalgo, 2008]. We took an average of the models listed in the appendix to form the model ensemble.

Drought index

We used the standardized precipitation index (SPI) as a measure of the relative dryness of each pixel in the spatial area of interest. For our study, we employed a non-parametric implementation of SPI to retain the spatial and temporal consistency of the original data [Farahmand and AghaKouchak, 2015]. SPI was used to describe precipitation in the context of the local climatology on a flexible temporal scale [Farahmand and AghaKouchak, 2015]. Since drought can be characterized by many timescales with regards to meteorological, soil moisture, and groundwater conditions, we chose to use 6-month SPI to represent seasonality without including brief wet or dry periods [WMO, 2012].

Quantitative methods

We first calculated the average temperature shift associated with each dryness threshold for each pixel. We used the United States Drought Monitor (USDM) classification scheme (D0, D1, D2, etc.) measured by SPI to delineate the drought severity thresholds. D0 begins with an SPI of -0.5, D1 begins with an SPI of -0.8, and D2 begins with an SPI of -1.3. For the D0 threshold, we isolated months that had an SPI value of -0.5 or lower and found the corresponding temperature average. To find the temperature shift between periods, we calculated the difference between temperature average associated with each period. We then summarized the temperature shifts within seven climatically consistent regions in the contiguous US. We used the Kolmogorov-Smirnov non-parametric test and Student's t-test to determine whether regional shifts under the drier conditions were significant in comparison to the average temperature change experienced in the area ($\alpha = 0.05$). We also studied the shifts by season to evaluate if seasonality affected the results from the overall analysis.

CHAPTER III

Results

Between the early and late 20th century CRU observations, the southern and eastern regions of the U.S. experienced higher temperature shifts under dry conditions than under all climate conditions (Figure 3-1). We observed that the Southern states displayed a similar pattern in the BCSD downscaled CMIP5 multi-model ensemble (Figure 3-1). The shifts in warming did not correspond exclusively with regions commonly identified as semi-arid or arid. In the observations, the spatial patterns also contrasted with the warming and cooling patterns that were observed between the early and late half of the 20th century. In the climate multi-model ensemble, the spatial patterns did not coincide with the north-south gradient of latitudinal heating predicted under the RCP 8.5 scenario as well. Instead of the northern regions experiencing greater shifts in comparison to the southern regions, our results displayed the opposite pattern. To deconstruct the spatial patterns presented, we displayed the shifts by region (Fig. 3-2 and Fig. 3-4). By region, the differences between the historical observations and model projections are more apparent. Historically, the northeastern region of the US showed the shift in dry-warm conditions, while CMIP5 models predicted an opposing shift in the entire upper half of the US.

The amplified shift between time periods could also be observed by plotting the temperature distributions. From the observations, the Southeastern region displayed a notable shift between temperatures under the average climate and temperatures under the D0 condition (Fig. 3-3). In the late 20th century, the temperature distribution under the D0 condition significantly increased the emphasis on warmer months in comparison to the average climate. The Southwest also displayed a shift between temperatures under the average climate and under the D0 condition (Fig. 3-5). Plots for the remaining regions displayed similar results to the box plot figures (Fig. A-1, A-2).

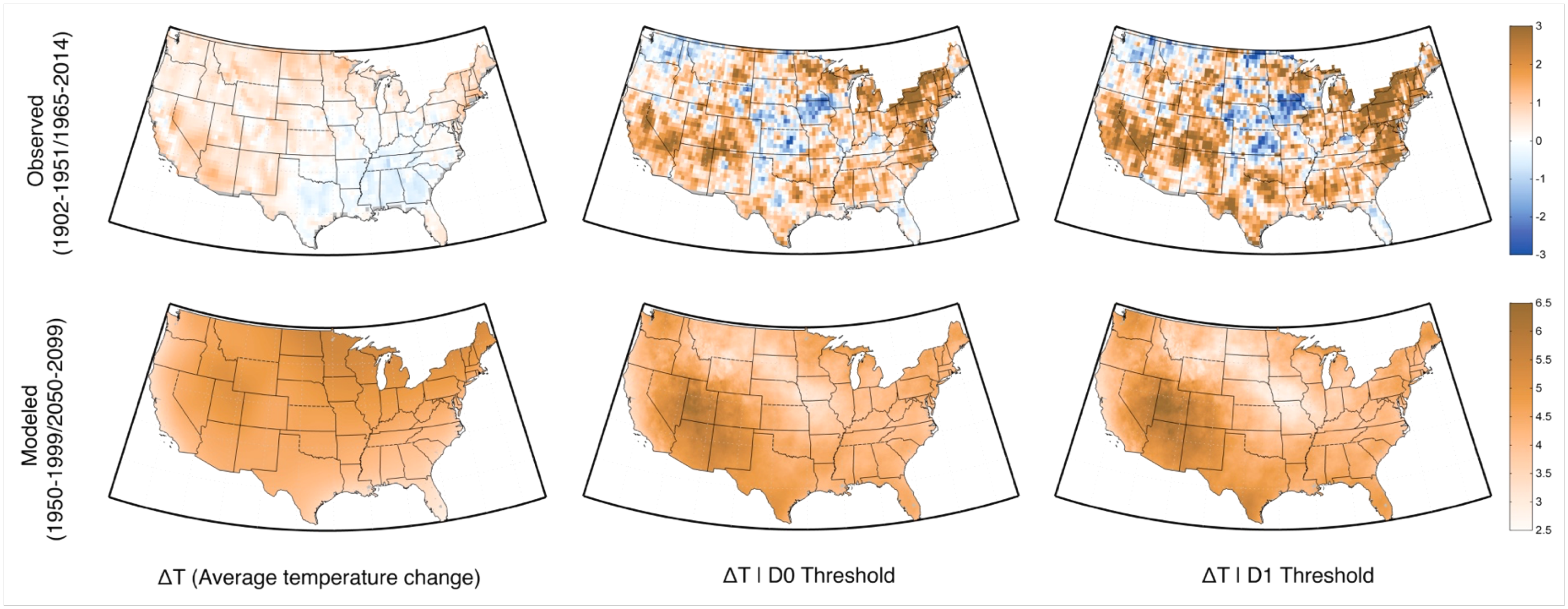

Figure 3-1. Gridded average temperature shift associated with each condition (average temperature change, conditions at or under the D0 dryness threshold, conditions at or under the D1 threshold).

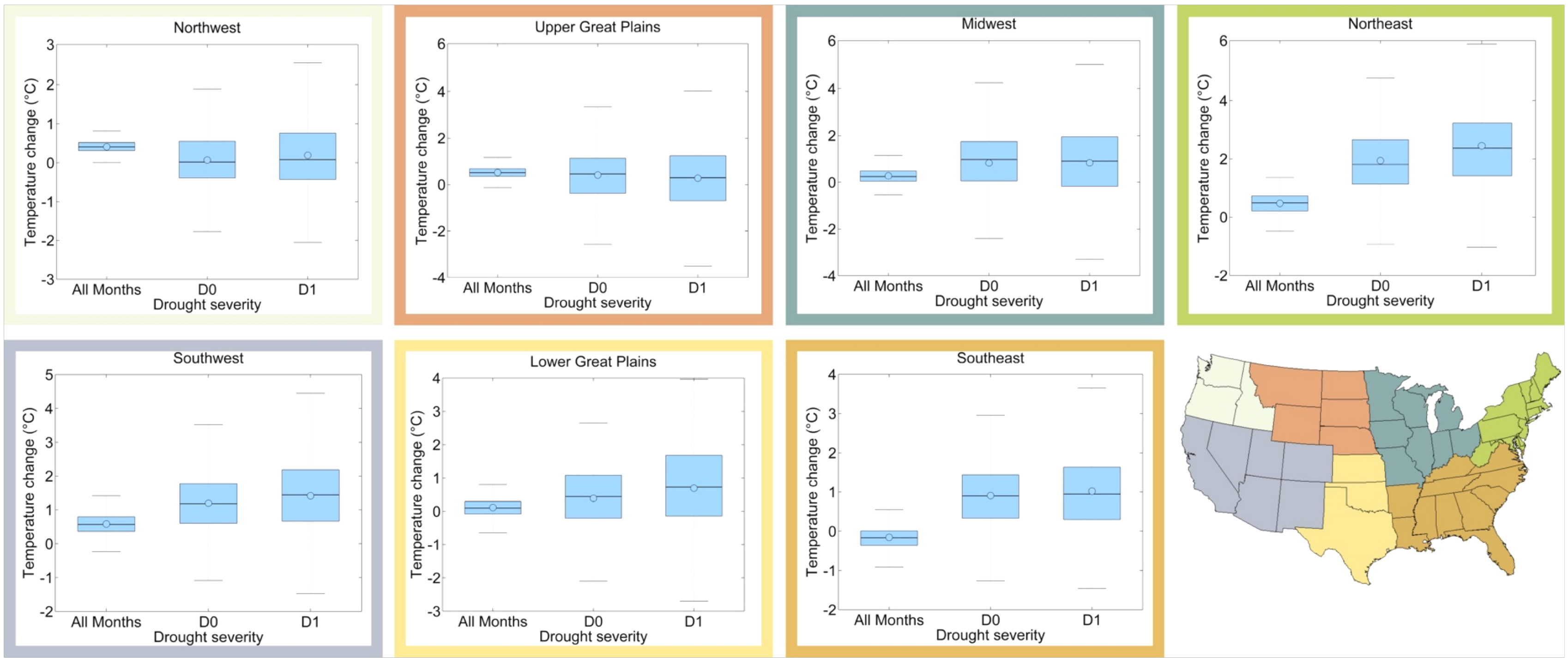

Figure 3-2. Regional box plots displaying the shifts corresponding to each condition for the CRU observations.

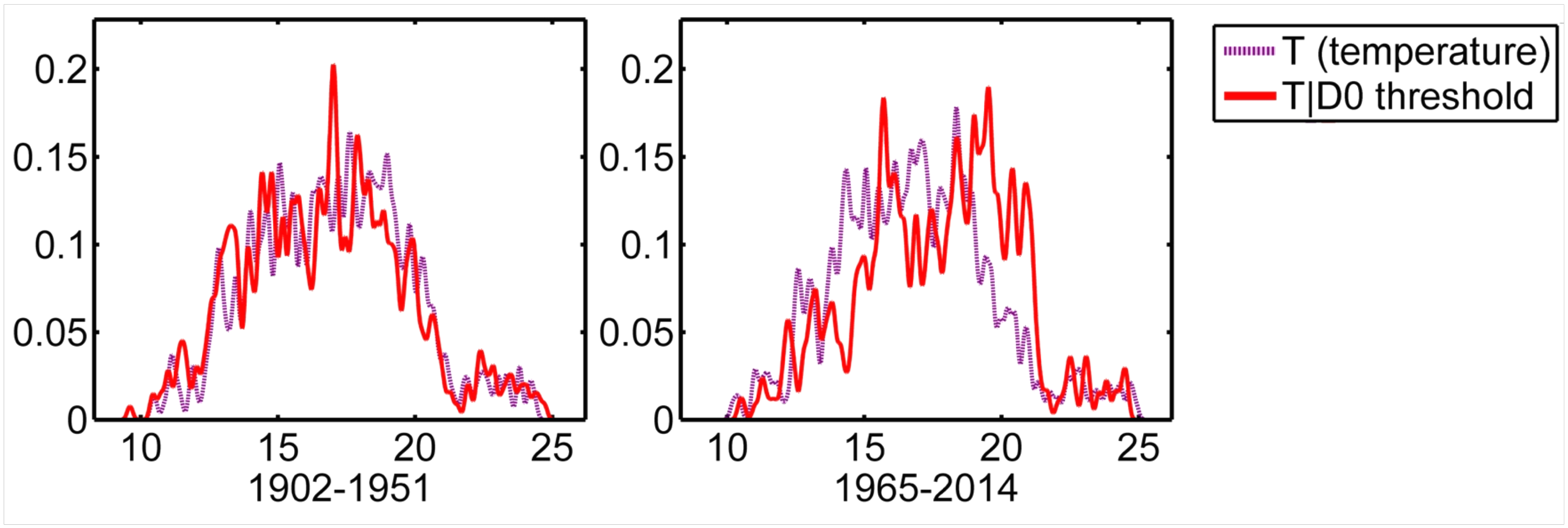

Figure 3-3. Distributional plots comparing the shifts between the D0 condition and the average climate for the Southeast region of CONUS.

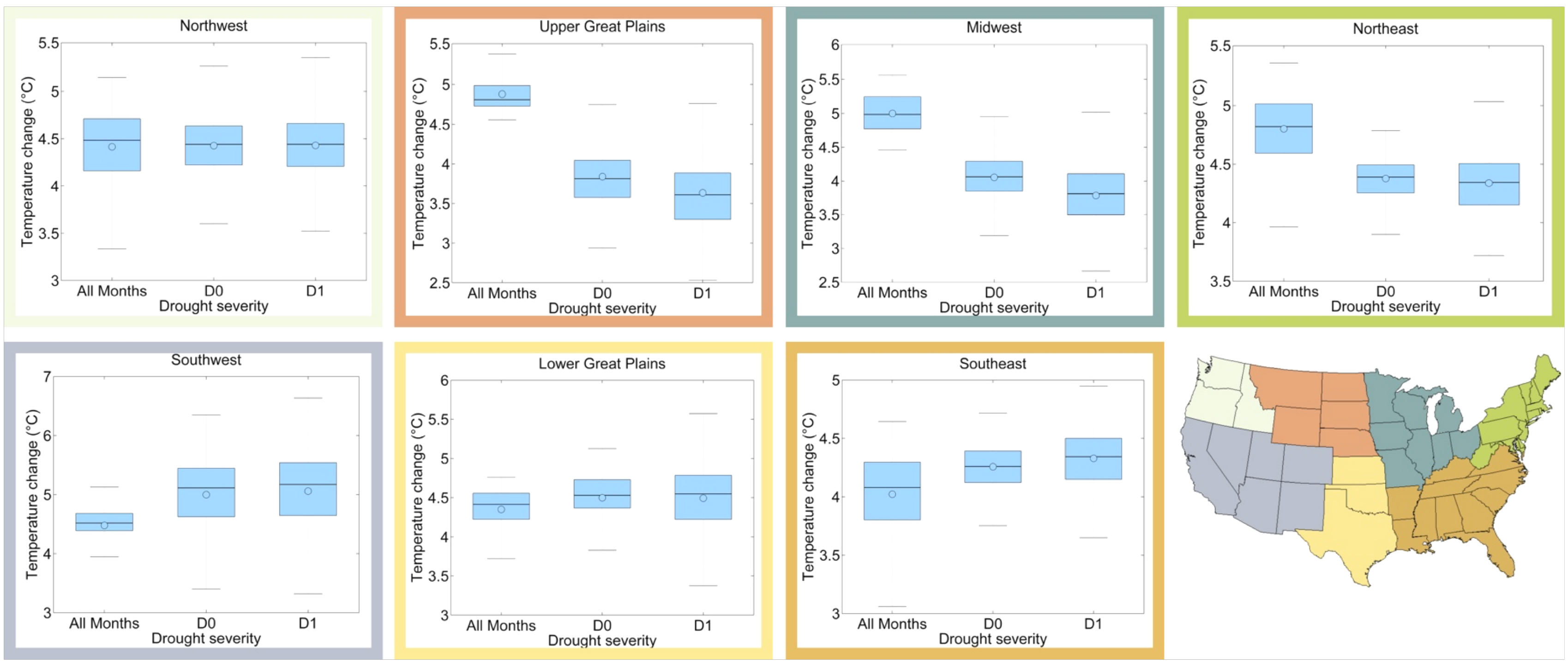

Figure 3-4. Regional box plots displaying the shifts corresponding to each condition for CMIP5 modeled projections.

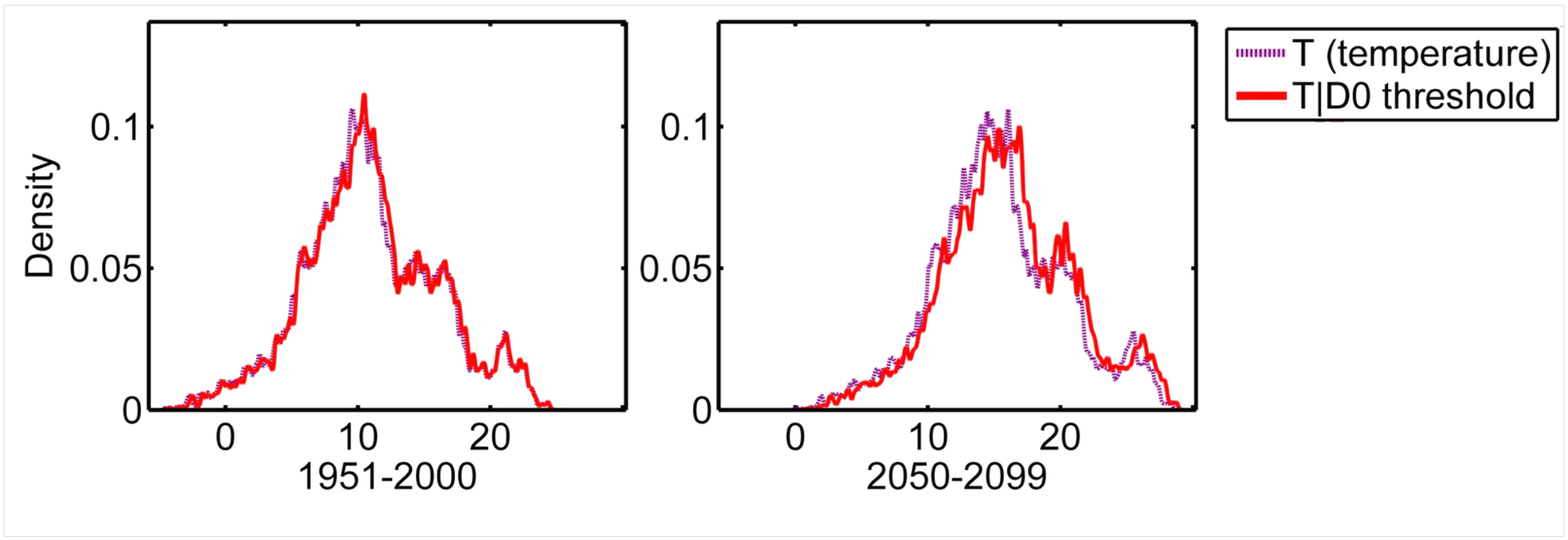

Figure 3-5. Distributional plots comparing the shifts between the D0 condition and the average climate for the Southwest region using the CMIP5 modeled projections.

By season, the historical data did not show large differences between the average temperatures in the two study periods (Fig. 3-6). Winter, spring and autumn seasons all displayed the dry-warming shift that the southern and eastern regions of the US showed.

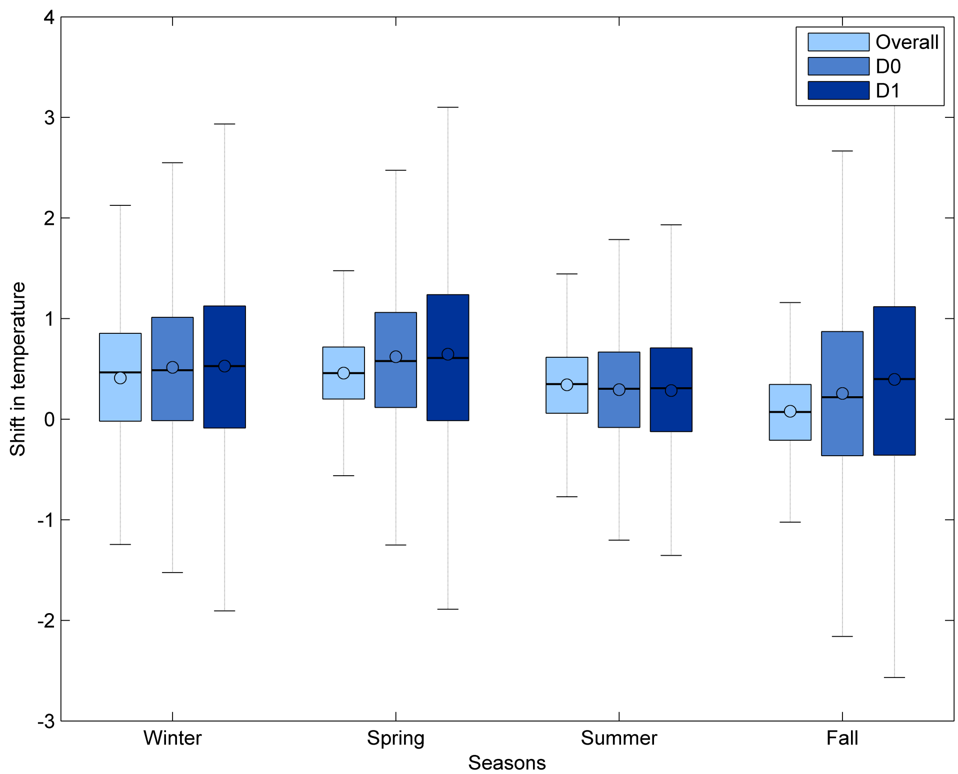

Figure 3-6. Boxplot displaying the shifts in historical temperature by season and condition for the contiguous US (CONUS).

From the multi-model ensemble, we found that the summer shift in temperature reflected the dry-warming pattern seen in the southern regions under the projected future (Fig. 3-7). This result implies that lower levels of precipitation from the preceding winter and spring seasons dominated the overall projected trend for the continental United States.

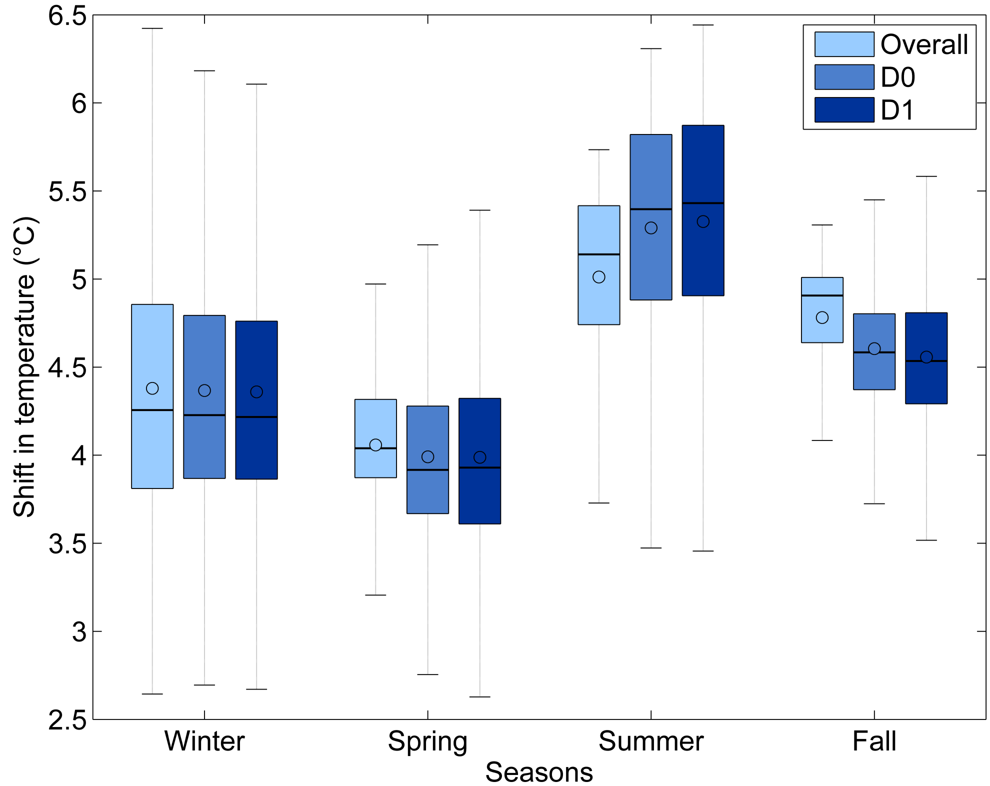

Figure 3-7. Boxplot displaying the shifts in projected temperatures by season and condition for the CONUS.

Discussion

We evaluated if dry temperatures were experiencing larger changes than the average climate. The CRU observations showed significantly higher temperature shifts during drought events in the southern and eastern states in comparison to the average climate. With the CMIP5 ensemble projections, we observed a similar pattern in the southern regions of the contiguous US. However, most of the northern states experienced lower temperature shifts during drought months in comparison to the average climate. The Kolmogorov-Smirnov test revealed significant differences between the shift seen from the average temperature and the shift seen under the D0 threshold for the two historical periods in all regions. T-testing matched the K-S test results. The K-S test also showed significant differences between the average temperature and D0 threshold shifts in comparing the future projections relative to the modeled past. T-testing showed that all regions excepting the Northwest showed significant differences between the dry and average temperature shifts for the projections relative to the modeled past.

Physical explanation of higher temperatures observed during dry conditions

Land surface conditions can physically explain the higher temperatures that are commonly seen during periods of drought. As mentioned earlier, periods of drought have instigated higher surface temperatures due to decreased evaporation and subsequent changes in the land surface energy balance [Chang and Wallace, 1987; Seneviratne et al., 2010; Livneh and Hoerling, 2016]. Soil moisture conditions control the sensible to latent heat ratio, and drier surfaces allow more incoming energy to increase the local temperature [Walsh et al., 1985; Huang and van den Dool, 1993; Seneviratne et al., 2010; Dirmeyer et al., 2013; Yin et al., 2014; Hansen and Sato, 2016]. In addition, the land experiences atmospheric feedbacks due to cloud cover, relative humidity, and other factors [Walsh et al., 1985; Huang and van den Dool, 1993].

Studies have established the relationship of temperature following precipitation to be the strongest during the summer months, especially in the lower Midwest [Madden and Williams, 1978; Karl, 1986; Huang and van den Dool, 1993, Koster et al., 2004; Seneviratne et al., 2010; IPCC, 2013]. The summer months see stronger correlations between the variables since there is a higher potential for a greater sensible heat flux, depending on precipitation, and thus, soil moisture conditions [Huang and van den Dool, 1993]. Regions that have a moderate soil moisture regime are more dependent on precipitation conditions, as fluctuations in water availability are more likely to influence the temperature [Koster et al., 2004]. Snowfall and snow cover also reduce temperatures during the winter months [Walsh et al., 1985]. Regions with widespread snow cover, such as the eastern United States, experience significant declines in local surface temperatures [Walsh et al., 1985].

Reasoning behind the shift in dry temperatures

Increases in drought occurrences associated with high temperatures have been documented in North America and Asia over the past century [Hao et al., 2013; Diffenbaugh et al., 2014; Chen and Sun, 2017]. Using model simulations of both natural and human forcings, Diffenbaugh et al. [2014] found the dry years were more likely to be warm as a result of human influences. Chen and Sun [2017] also established that anthropogenic influences were responsible for the observed warming trend during dry time periods in China. The increase in this association of dry events with high temperatures is consistent with the historical changes we have seen in many of the regions in the US.

Higher temperature shifts between early and late 20th century drought periods may be a result of changes occurring in the overall climate. Increases in drought frequencies due to the behavior of the Pacific Decadal Oscillation and the Southern Oscillation Index may have produced the southern and eastern patterns in the historically observed shift [Kam et al., 2014]. In addition, atmospheric circulation changes due to climate change may be contributing to the spatial patterns in the observed shift [IPCC, 2007]. The higher latitudes in the Northern Hemisphere have experienced increased precipitation [Dore, 2005]. This increase in precipitation may have dampened changes in the sensible heat flux in the northern states. In contrast, annual snow-cover extent has shrunken ten percent since the

1960s [Dore, 2005]. The occurrence of snow cover significantly influences local temperatures due to albedo, emissivity, and thermal conductivity properties of snow [Zhang, 2005]. Snowmelt also acts as a latent heat sink, further reducing temperatures [Zhang, 2005]. Thus, a decrease in snow-cover extent could be associated with an increase in surface temperature, corresponding with the dry temperature shift in the eastern states.

Models have also projected changes in water vapor concentrations and changes throughout the hydrologic cycle due to climate change, causing shifts in the distributions of precipitation and evaporation around the world [Held and Soden, 2006; Solomon et al., 2009]. ENSO has been projected to remain the dominant climate mode through the 21st century, and the variability in ENSO-associated rainfall has been projected to increase [IPCC, 2013]. Zhou et al. [2014] found an eastward shift in the ENSO associated PNA pattern due to projected climate change, which may impact changes in the distribution of precipitation and thus the spatial patterns seen in the projections.

The spatial patterns where larger shifts in temperature are projected to occur can be traced back to individual variables in the CMIP5 model ensemble. Large decreases in summer soil moisture are projected to occur in the southern regions of the US, which will affect corresponding temperatures [Seneviratne et al., 2010; Dirmeyer et al., 2013]. During the winter months, CMIP5 simulations also projected slight decreases in precipitation in southern US [Sheffield et al., 2014]. Projected increases in temperatures over mid to higher latitudes of North America increase the amount of precipitation falling as rain instead of snow [IPCC, 2007]. However, the state of precipitation falling as rain or snow may or may not significantly affect surface temperatures that follow. This is a research question that has potential to be studied in detail.

Effect of seasonality

Considering the 20th century US climate division precipitation record, Finkelstein and Truppi [1991] examined the seasonal patterns of the spatial distribution of rainfall. Historically, winter rainfall maximums are seen along the northern West Coast and summer rainfall maximums along the northern Midwest, while the southern and eastern regions of the US do not have a seasonal bias [Finkelstein and Truppi, 1991]. Regions with relatively low winter rainfall can be associated with the regions that experienced the intensification of the warming temperature-low precipitation association.

Through a percentile-based analysis, Pryor and Schoof [2008] observed relative shifts in the seasonality of precipitation, plotting the spatial distribution of whether the 50th percentile of the annual rainfall for the year was achieved earlier or later in comparison to earlier records. Between 1911-1940 and 1971-2000, there was an observable spatial pattern where the eastern states observed earlier 10th-50th percentiles of precipitation, the Great Plains observed earlier 50th-75th percentiles of precipitation, and the western and southern states observed earlier 50th-90th percentiles of precipitation [Pryor and Schoof, 2008]. Changes in the timing of precipitation control subsequent evapotranspiration, infiltration or runoff, which is reflected in the results that we observed in our own historical analysis [Pryor and Schoof, 2008]. Climate scenarios also project changes in seasonality, which may produce deviations from the historical spatial pattern of the warm shift between drought periods [Finkelstein and Truppi, 1991].

CMIP5 model ensemble accuracy

In some areas, the CMIP5 models may have inconsistent physical interpretations since surface and meteorological drivers are represented differently in each model [Livneh and Hoerling, 2016]. Although the models capture the large-scale temperature patterns in the globe, there are systematic biases in tropical circulation patterns, as well as in tropical-extratropical patterns from PDO variability [IPCC, 2013; Sheffield et al., 2014]. Projections of ENSO timing and variability also suffer from model biases due to the model rendering of deep convective, cloud feedback, and other physical mechanisms [IPCC, 2013]. In addition, the CMIP5 ensemble can represent the general winter and spring sea surface temperature patterns, but have trouble with Ekman current transport and stratus clouds, causing warm temperature biases in the Pacific and Atlantic oceans [Sheffield et al., 2014]. Cold biases have also been identified across both the Pacific and Atlantic oceans, which influence dependent climate variables [Sheffield et al., 2014]. The known errors in the CMIP5 output prevent us from drawing concrete conclusions from the shifts that we have observed in the projections.

CHAPTER IV

Conclusions and Future Directions

From our results, we have established that droughts have been experiencing amplified temperature increases relative to the average climate in the southern and eastern regions of the United States. The observed spatial pattern of the drought conditioned temperature shift can largely be explained by shifts in precipitation and snow cover. In projections, droughts will be significantly warmer than average conditions across the southern region of the U.S., as dictated by changes in the amount of precipitation and soil moisture available. The magnitude of the drought conditioned temperature shift is largest in the summer months for future projections by CMIP5 models. The effect of the 6-month moisture conditions preceding summer months may dictate how future droughts in the US behave, and winter and spring precipitation should be studied in detail in conjunction with summer temperatures. Summer land surface conditions due to persistent solar radiation should also be investigated in further detail to see how surface conditions will shift in response to climate change. The patterns associated with warming temperatures and waning precipitation will be important in evaluating future projections of drought occurrences and understanding regional changes in our climate.

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APPENDIX A: CMIP5 Climate Models

Modeling Center	Institute ID	Model Name
Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	CSIRO-BOM	ACCESS1.0 ACCESS1.3
Beijing Climate Center, China Meteorological Administration	BCC	BCC-CSM1.1 BCC-CSM1.1(m)
Canadian Centre for Climate Modeling and Analysis	CCCMA	CanESM2
National Center for Atmospheric Research	NCAR	CCSM4
Community Earth System Model Contributors	NSF-DOE-NCAR	CESM1(BGC) CESM1(CAM5)
Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC	CMCC-CM
Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation Avancée en Calcul Scientifique	CNRM-CERFACS	CNRM-CM5
Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	CSIRO-QCCCE	CSIRO-Mk3.6.0
LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University	LASG-CESS	FGOALS-g2
The First Institute of Oceanography, SOA, China	FIO	FIO-ESM
NOAA Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-CM3 GFDL-ESM2G GFDL-ESM2M
NASA Goddard Institute for Space Studies	NASA GISS	GISS-E2-R
National Institute of Meteorological Research/Korea Meteorological Administration	NIMR/KMA	HadGEM2-AO
Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espacials)	MOHC (additional realizations by INPE)	HadGEM2-CC HadGEM2-ES
Institute for Numerical Mathematics	INM	INM-CM4
Institut Pierre-Simon Laplace	IPSL	IPSL-CM5A-LR

		IPSL-CM5A-MR IPSL-CM5B-LR
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC	MIROC-ESM MIROC-ESM-CHEM
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC	MIROC5
Max-Planck Institut für Meteorologie (Max Planck Institute for Meteorology)	MPI-M	MPI-ESM-LR MPI-ESM-MR
Meteorological Research Institute	MRI	MRI-CGCM3
Norwegian Climate Centre	NCC	NorESM1-M NorESM1-ME

APPENDIX B: Supplementary figures

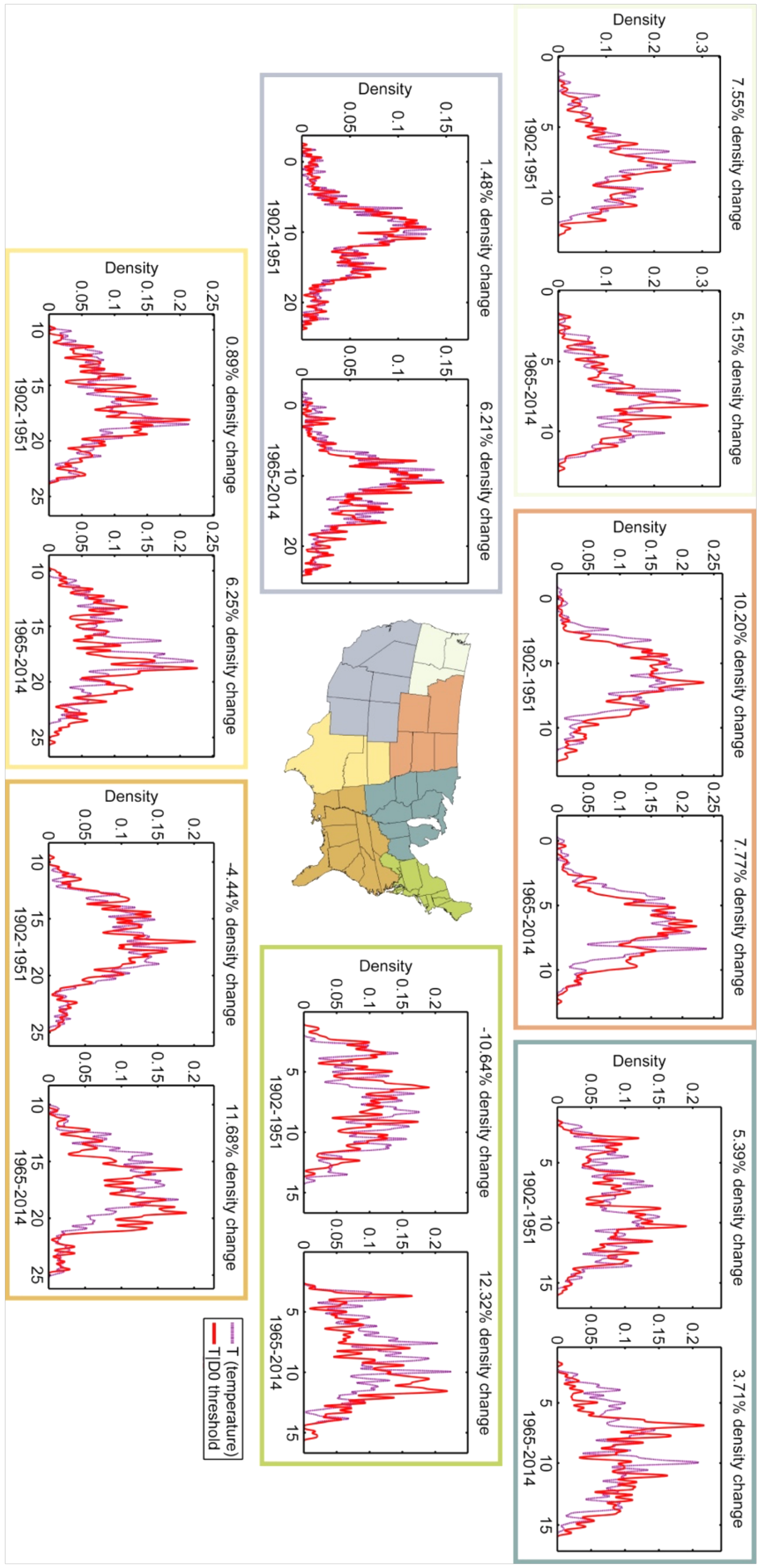

Figure A-1. Distributional plots comparing the shifts between the D0 condition and the average climate for all regions using the CRU observations.

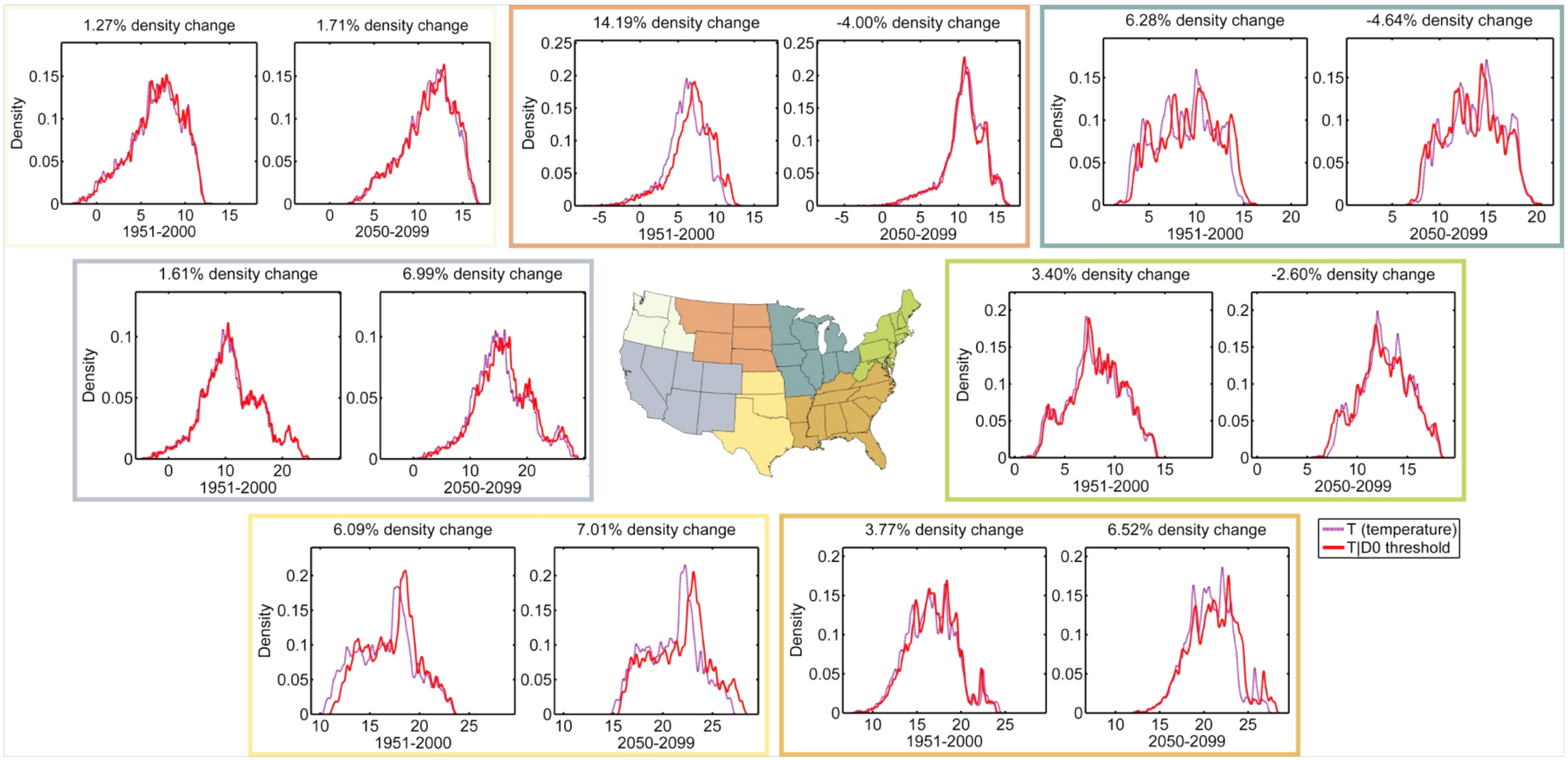

Figure A-2. Distributional plots comparing the shifts between the D0 condition and the average climate for all regions using the CMIP5 modeled projections.