Effects of 0.5°C Less Global Warming On Climate Extremes in The Contiguous United States

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Abstract

The Intergovernmental Panel on Climate Change (IPCC) suggests limiting global warming to 1.5°C compared to 2°C would avoid dangerous impacts of anthropogenic climate change and ensure a more sustainable society. As the vulnerability to global warming is regionally dependent, this study assesses the effects of 0.5°C less global warming on climate extremes in the United States. Eight climate extreme indices are calculated based on Coupled Model Intercomparison Project - phase 5 (CMIP5), and North American - Coordinated Regional Climate Downscaling Experiments (NA-CORDEX) with and without bias correction. We evaluate the projected changes in temperature and precipitation extremes, and examine their differences between the 1.5°C and 2°C warming targets. Under a warming climate, both CMIP5 and NA-CORDEX show intensified heat extremes and reduced cold extremes across the country, intensified and more heavy precipitation in large areas of the North, prolonged dry spells in some regions of the West, South, and Midwest, and more frequent drought events in the West. Results suggest that the 0.5 °C less global warming would avoid the intensification of climate extremes by 32~46% (35~42%) for heat extremes intensity (frequency) across the country and, by 23~41% for heavy precipitation intensity in the North, South, and Southeast. The changes in annual heavy precipitation intensity are mainly contributed by winter and spring. However, impacts of the limited warming on the frequency of heavy precipitation, dry spell, and drought frequency are only evident in a few regions. Although uncertainties are found among the climate models and emission scenarios, our results highlight the benefits of limiting warming at 1.5°C in order to reduce the risks of climate extremes associated with global warming.

1. Introduction

Extreme climate events and their changes have drawn increasing attention under the background of global climate change due to their potentially severe impacts on human societies and ecosystems (Fischer and Knutti 2015). Observations and climate models suggest an intensification of temperature and precipitation extremes in a warming climate (Allan and Soden 2008; Alexander et al. 2006; Sillmann et al. 2013). According to the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report, global temperature will continue to increase if greenhouse gas emissions continue unabated (Collins et al. 2013). Under different Representative Concentration Pathways (RCP) scenarios, the global surface temperature change by the end of the 21st century is likely to exceed 1.5°C above pre-industrial levels for RCP4.5, RCP6.0, and RCP8.5, and the warming is likely to exceed 2°C for RCP6.0 and RCP8.5 (IPCC 2014). With increasing radiative forcing, more frequent high-temperature extremes and heavy precipitation events are expected to occur in the future (Sillmann et al. 2013; Fischer and Knutti 2015). Over the United States, significant changes have been found in hot and cold temperature extremes, heavy precipitation, and droughts based on the Coupled Model Intercomparison Project 5 (CMIP5) future climate projections (Wuebbles et al. 2014). These changes are also documented in high-resolution downscaled climate projections, especially for the increases in frequency and intensity of heat waves (Zobel et al. 2017) and heavy precipitation (Prein et al. 2016).

To avoid more severe impacts from climate change, the Paris Agreement aims to strengthen the global response to the threat of climate change by keeping a global temperature increase well below 2°C relative to pre-industrial levels, and also to make further efforts to limit the temperature increase to 1.5°C. An IPCC special report, Global Warming of 1.5°C, has discussed the impacts of global warming of 1.5°C above pre-industrial levels (IPCC 2018). Compared to 2°C warming, limiting global warming to 1.5°C would lead to global differences in temperature extremes with high confidence, and limit risks of increased heavy precipitation events on a global scale and in some regions with medium confidence (Hoegh-Guldberg et al. 2018). Although the report has thoroughly investigated the changes in climate extremes over different regions of the world, there are several limitations that hinder a comprehensive assessment of climate change impacts on the national scale, such as the contiguous United States.

First, although much has been learned from the climate projections from global climate models (GCMs) in CMIP5 (Karmalkar and Bradley 2017; Hoegh-Guldberg et al. 2018), few studies have considered using regional climate models (RCMs) to understand the consequences of the 0.5°C less warming on regional extreme events. The RCMs are expected to improve the quality of the climate information at regional scales, because they can represent the local forcings (e.g. complex topography and land-surface characteristics, Giorgi and Gutowski 2015), and better capture climate processes at fine scales, especially for precipitation extremes (Frei et al. 2006). For instance, Gibson et al. (2019) found that RCMs show a better performance for certain precipitation indices (such as, simple daily precipitation intensity index) than GCMs, which generate too frequent low-intensity precipitation, also known as the “drizzle” issue. Therefore, it is worthwhile to also investigate the climate extremes using downscaled climate simulations from the RCMs. Second, uncertainties in the climate models (either GCMs or RCMs) introduce biases in subsequent impact simulations. Bias correction of climate model output is necessary to provide reliable and robust future projections of the means of climate variables for use in impact assessment (Navarro-Racines et al. 2020). However, current impact assessments of 0.5°C less warming have not included the bias-corrected climate projections. Lastly, the impacts of climate change are regionally dependent (Sillmann et al. 2013; Peng et al. 2019). For instance, the projected change in precipitation extremes varies in different regions of the contiguous US (Singh et al. 2013). Therefore, it is necessary to conduct the impact assessment at sub-national scales.

To overcome the limitations discussed above, this study aims to provide a comprehensive assessment of the effects of 0.5°C less global warming on climate extremes over the contiguous US using three sets of climate simulations, including raw GCM output, raw RCM output, and bias-corrected RCM output. The primary question is how 0.5°C less global warming influences climate extremes in the US. We will examine the robustness of climate change impacts among the three datasets, and analyze the changes in climate extremes in different regions of the US. Results are presented in Sect. 3. Discussions and conclusions are given in Sect. 4.

2. Data And Methodology

In this study, we analyze eight climate extreme indices derived from three climate data sets to understand the changes in temperature and precipitation extremes if reducing future globally averaged warming from 2.0°C to 1.5°C. Although the bias-corrected RCMs presumably would provide a better representation of regional/local climate phenomena and their variability through downscaling and bias correction, analysis using the three climate datasets would allow us to evaluate the possible influence of downscaling (from GCM to RCM) and bias correction (from raw RCM to bias-corrected RCM) on identified changes in climate extremes. Previous assessment on the impacts of 0.5°C less warming relies on GCMs without considering bias correction (e.g., Karmalkar and Bradley 2017). In this study, through the comparison among the three datasets (CMIP5, raw NA-CORDEX, and bias-corrected NA-CORDEX), we will be able to identify the consistency of the datasets or added information of downscaling or bias correction.

2.1 CMIP5 data

Figure 1 shows the information about 19 CMIP5 models, which provide monthly mean air temperature, daily maximum and minimum temperature, and daily precipitation from the historical and future simulations under the RCP 8.5 pathway. The 19 models are used because they are available with daily precipitation and temperature output. Only the first ensemble run (e.g., r1i1p1) is used for each model. Although some models have more than one realization available, we only use the first ensemble member to keep all GCMs being equally weighted in multimodel analysis. Previous studies also use the first ensemble member in climate extreme assessment (e.g., Sillmann et al. 2013; Ting et al. 2015; Peng et al. 2019). Meanwhile, only one ensemble member of GCMs participating in the CMIP5 are used as boundary conditions of the regional models in NA-CORDEX. The historical simulations are forced by observed atmospheric composition changes reflecting both anthropogenic and natural sources. The RCP 8.5 scenario assumes high population growth and high energy demands without climate change policies. It corresponds to the pathway with the highest greenhouse gas emissions, brought about by a radiative forcing of 8.5 W/m^2 in 2100 (Riahi et al. 2011). For the multimodel ensemble analysis, all the CMIP5 output are regridded to a common latitude-longitude grid (1°× 1°) using the bilinear interpolation method.

2.2 NA-CORDEX

The North American - Coordinated Regional Climate Downscaling Experiments (NA-CORDEX) provide a set of regional climate simulations from multiple GCM-RCM combinations, which use different RCMs to downscale the GCM simulations from the CMIP5 archive over a domain covering most of North America. Details of the NA-CORDEX dataset can be found at Mearns et al. (2017). Table 1 shows the details of the available 13 GCM-RCM combinations used in this study. There are six GCMs (CanESM2, EC-EARTH, GFDL-ESM2M, HadGEM2-ES, MPI-ESM-LR, and MPI-ESM-MR) providing lateral boundary conditions for six RCMs (CanRCM4, CRCM5-UQAM, RCA4, HIRHAM5, RCA4, and RegCM4). Previous studies show that NA-CORDEX models generally capture the observed large-scale orographic precipitation enhancement features across the western US (Mahoney et al. 2021) and large-scale weather types across the US (Prein et al. 2019). Daily maximum and minimum temperature and daily precipitation are obtained from the 13

GCM-RCM downscaled simulations for the historical period (1950–2005) and the RCP 8.5 future period (2006–2100).

Table 1
List of 13 NA-CORDEX GCM-RCM combinations used in this study.

Model combination	RCM	GCM	Available resolutions
1	CanRCM4	CanESM2	50 km, 25 km
2	CRCM5-UQAM	CanESM2	50 km, 25 km
3	CRCM5-UQAM	MPI-ESM-LR	50 km
4	CRCM5-UQAM	MPI-ESM-MR	50 km, 25 km
5	HIRHAM5	EC-EARTH	50 km
6	RCA4	CanESM2	50 km
7	RCA4	EC-EARTH	50 km
8	RegCM4	GFDL-ESM2M	50 km, 25 km
9	RegCM4	HadGEM2-ES	50 km, 25 km
10	RegCM4	MPI-ESM-LR	50 km, 25 km
11	WRF	GFDL-ESM2M	50 km, 25 km
12	WRF	HadGEM2-ES	50 km, 25 km
13	WRF	MPI-ESM-LR	50 km, 25 km

The NA-CORDEX also provides bias-corrected climate simulations for each GCM-RCM combination, which are adjusted using a multivariate quantile-mapping method against a gridded daily observational dataset (Cannon 2017). In this study, we include the dataset that has been bias-corrected using METDATA, which provides daily high-resolution (1/24th degree) surface meteorological data covering the contiguous US (Abatzoglou 2013). Although the changes in quantiles of each variable are preserved in the quantile mapping approach, the projected changes are still affected by the bias correction. Previous studies (Li et al. 2010) also documented the influence of quantile mapping bias correction on temperature and precipitation projections, especially their extremes. The bias correction of NA-CORDEX can reduce most of the bias in mean temperature and extreme values, and provides effective correction of frequency, intensity, and total amount of precipitation (McGinnis and Mearns 2016). Meanwhile, uncertainty remains in the bias-correct outputs due to the choice of observational datasets for training (McGinnis et al. 2019). All the model output (raw and bias-corrected) have been interpolated into a common latitude-longitude grid (0.5°× 0.5°, which is approximately at a 50-km resolution). Additionally, to evaluate the added values of higher spatial resolutions in simulated climate extremes, the CORDEX output at a 25-km resolution is also included in our analysis.

2.3 Climate Indices

We use eight climate indices to quantify the intensity and frequency of temperature and precipitation extremes (Karl et al. 1999). The definitions of the indices are shown in Table 2. These indices are derived from daily temperature and precipitation from the CMIP5 and NA-CORDEX archives. For TX90p and TN10p (percentage of days when daily maximum temperature > 90th percentile, and percentage of days when daily minimum temperature < 10th percentile), the 10th and 90th percentile references are calculated based on the values for the base period 1971–2000.

Table 2
Definition of eight climate indices used in this study. Details of the first seven indices can be found at Climdex (https://www.climdex.org/learn/indices/).

Climate index	Definition	Unit
TXx	Annual maxima of daily maximum temperature	K
TNn	Annual minima of daily minimum temperature	K
TX90p	Percentage of days when daily maximum temperature > 90th percentile	%
TN10p	Percentage of days when daily minimum temperature < 10th percentile	%
Rx5day	Annual/seasonal maximum consecutive 5-day precipitation	mm
R10mm	Annual/seasonal count of days when daily precipitation ≥ 10mm	days
CDD	Annual maximum number of consecutive days with daily precipitation < 1mm	days
drought frequency	Percentage of months when standardized precipitation index < -0.8	%

Additionally, to better quantify the changes in drought events, a 24-month standardized precipitation index (SPI) is calculated based on monthly precipitation using gamma distribution fitting (Guttman 1999). The 24 months of SPI are the current month and preceding 23 months. The 24-month time scale is chosen because it reflects long-term precipitation patterns. The drought frequency is defined as the percentage of months with SPI below − 0.8 each year. The SPI below − 0.8 indicates moderate or more severe drought according to US Drought Monitor classification. We noted that the detected changes in drought frequency exhibit a very consistent spatial pattern but with different magnitude (not shown) if using different SPI (e.g., 6 months versus 24 months) or different drought thresholds. Therefore, the choice of these values does not affect the identified impacts of 0.5°C less warming.

Because some indices are defined based on certain thresholds, such as R10mm is the annual count of days when daily precipitation is more than 10 mm, we have tested the sensitivity of results to the threshold used in the index. Results are consistent among the choices of different thresholds (not shown).

2.4 Detection of 1.5°C and 2°C global warming

There are different ways for identifying the 1.5°C and 2°C global warming targets, such as sub-selecting models based on global temperature response, and sampling at the time of global temperature increments (James et al. 2017). Considering the advantages and data availability, we use the time sampling approach to identify the time when 1.5°C and 2°C global warmings are reached and examine regional climate changes which occur at that date (James et al. 2017). To identify the timing of 1.5°C and 2°C warming relative to pre-industrial levels, a 21-year window is applied to the time series of average annual global temperatures in each GCM. This approach can eliminate uncertainties associated with climate sensitivities from the different models and reduce uncertainties related to internal variability, and has been used in many studies (Schleussner et al. 2016; James et al. 2017; Peng et al. 2019; Tamoffo et al. 2019). For each model, we calculate the difference in global temperature between the pre-industrial period (1860–1880) from the historical simulation and a 21-year moving window from the RCP8.5 projection. Then we will be able to identify the two years when the warming reaches 1.5°C and 2°C, respectively (shown in Fig. 1). The same window size (or even a smaller window size) is used in previous studies to identify the timing when the global-mean temperature change exceeds a certain threshold (Anderson 2012; Peng et al. 2019).

Changes in climate extremes under future warming are computed as the differences in climate indices between the present reference period (1986–2005) and the identified 1.5°C (or 2°C) warming periods; the differences between the 2°C and 1.5°C warming periods, which are the 21-year windows surrounding the identified years shown in Fig. 1, are considered the effects of 0.5°C less global warming. Following the methodology in Li et al. (2019) and Peng et al. (2019), the reduced intensification of climate extremes will be calculated as

$$\text{Avoided intensification} = \frac{E1.5 - E2.0}{E2.0} \qquad \text{(Eq. 1)}$$

where E1.5 and E2.0 are the changes in climate extremes under the 1.5°C and 2°C global warming targets, respectively.

For each of the NA-CORDEX models, the timing of 1.5°C and 2°C global warming is assumed to be the same as its forcing GCM. For instance, the GFDL-ESM2M-WRF climate projection will use the year 2035 as the timing of 1.5°C global warming and the year 2051 as the time of 2.0°C global warming (according to Fig. 1).

We calculate the multimodel ensemble median of all available CMIP5 or NA-CORDEX models to quantify the future change in climate extremes. To assess its significance, the detected change is considered as "robust" when at least 75% of the models agree on the sign of the change. Similar strategies have been adopted in previous studies to assess the robustness of future climate change (Maloney et al. 2014; Peng et al. 2019; Chen 2020). Additionally, the study area is divided into nine regions, according to the defined climatically consistent regions of the contiguous US (Karl and Koss, 1984), for regional-scale analysis of the projected climate extremes (Fig. 2).

3. Results

3.1 Changes in temperature extremes

Figure 3 shows the projected changes in TXx, which depicts the intensity of hot extremes. Both CMIP5 and the raw NA-CORDEX suggest an overall increase in TXx throughout the country at the 1.5°C and 2.0°C warming levels. The intensified TXx is stronger in CMIP5 than that in the raw NA-CORDEX. Due to the observed cooling in summer temperature over the Midwest (Mueller et al. 2015), observation-based bias corrections lead to less warming in TXx in the bias-corrected NA-CORDEX compared to the raw NA-CORDEX (Figure 3c,f), but the increase in TXx is even stronger in other regions. Effects of 0.5 °C less global warming on TXx are shown in Figures 3g-i. Despite the discrepancies in the projected changes (Figures 3a-f), all three datasets show significant decreases in TXx with 0.5°C less global warming. The averaged decrease in TXx across the country is -0.8°C, -0.8°C, -0.7°C based on the CMIP5, raw NA-CORDEX, and bias-corrected NA-CORDEX, respectively. Therefore, the dynamic downscaling or bias correction does not play a substantial role in the average changes in hot extreme intensity.

Figures 4a-c show the projected changes in TX90p, which describes the frequency of hot extremes. Under the 2°C global warming, there is a significant increase in TX90p, especially over the southern US. However, the CMIP5 models suggest a stronger increase in the southeast, while the bias-corrected NA-CORDEX suggests a stronger increase in the southwest. From the 2°C warming to 1.5°C warming, the hot extremes become less frequent, especially over the southeastern US (Figures 4d-f). Despite the slight regional difference, the three datasets show similar average changes in TX90p (about -3%), indicating nearly eleven fewer days annually with daily maximum temperature above the 90th percentile if there is 0.5°C less warming. The reduced TXx and TX90p suggest that the intensity and frequency of hot extremes would be reduced if the global mean temperature increase is limited 1.5°C. Consequently, impacts from 0.5°C less warming include reduced extreme heat exposure and likely more overall positive human health outcomes. This finding is particularly important as exposure risk to extreme heat in the U.S. is disproportionately high among groups with the most limited adaptive capacity (Guirguis et al. 2018; Madrigano et al. 2018; Voelkel et al. 2018). Extreme heat is also a serious health risk for agricultural workers in the U.S. (Culp and Tonelli, 2019), a group that often does not have access to proper healthcare (Magaña and Hovey, 2003; Hoerster et al. 2011).

The changes in intensity and frequency of cold extremes (TNn and TN10p) are shown in Figure 5. Under the 2°C global warming, TNn shows a much larger change than the change in TXx. The increase in the minima of daily minimum temperature exceeds 3°C in most of the areas. The three datasets show a good agreement, but NA-CORDEX presents more spatial details of the changes. Meanwhile, the frequency of cold extremes decreases significantly, with the greatest reduction over the western US. The magnitude of the reduced frequency in cold extremes is relatively small compared with increased frequency in hot extremes (Figures 4a-c). With 0.5°C less global warming, there are reduced changes in TNn and TN10p. Over the contiguous US, the warming in TNn would decrease by 1.0°C in CMIP5 and 1.2°C in NA-CORDEX. The average increase in TN10p is 1.2% based on the three datasets, indicating about four more days annually with daily minimum temperature below the 10th percentile if there is 0.5°C less warming. As global warming will make cold extremes less intense and less frequent, the 0.5°C less warming will increase the intensity and frequency of cold extreme events. Therefore, there can be increased risks of cold-related mortality for human beings and frost damage for plants.

3.2 Changes in precipitation extremes

Figure 6 shows the projected changes in two indices of heavy precipitation (Rx5day and R10mm). The former is the annual maximum 5-day rainfall, potentially related to extreme precipitation events in some regions; the latter is the number of heavy precipitation days (Zhang et al. 2011). The index Rx5day increases in most of the areas on the 2.0°C warming level, suggesting intensified precipitation in a warming climate, especially for the heavy precipitation events. The three datasets exhibit a good agreement in increased Rx5day, but only bias-corrected NA-CORDEX shows an evident decrease in limited areas in Texas and New Mexico. The two NA-CORDEX datasets show a greater increase in Rx5day over the mountainous regions in the western US than CMIP5, which is also documented in previous downscaling studies (e.g., Meyer and Jin 2017). The intensification of precipitation events will generally be reduced if there is 0.5°C less warming, with a stronger reduction over the central US. The average Rx5day would decrease by 3% across the country. If examining the changes in actual precipitation amount (in mm, shown in Figure S1), the heavy precipitation intensity can be reduced by up to 10 mm/5-day, especially over the Midwest.

The projected changes in the frequency of heavy precipitation (R10mm) are shown in Figures 6g-l. Under the 2.0°C global warming climate, both CMIP5 and NA-CORDEX present more frequent heavy precipitation in the North but less frequent events in the South. However, NA-CORDEX shows decreased R10mm in large areas of the southern US, and bias correction introduces a less increase (or even a decrease) in R10mm over the northwestern US compared to the raw CORDEX. The 0.5°C less warming does not exert consistent effects on R10mm in many regions of the country except for the Northwest and the northern Plains, where there are 1~1.5 fewer days with heavy precipitation annually. The changes in Rx5day and R10mm suggest that there is high confidence that intensity and frequency of heavy precipitation will increase under a warming climate, especially over the northern US. Heavy precipitation is linked to both flash and riverine flooding, therefore reduction of heavy precipitation frequency from 0.5°C less warming, given no change in development, floodplain management, and policy, will decrease flood risk. Reduction of heavy precipitation, particularly in the Midwest and northern Plains regions, decreases top soil erosion and nutrient runoff from agricultural fields, thereby maintaining good soil health and surface water quality (Morton et al. 2015).

Figure 7a-f shows the changes in dry spell. Under a warming climate, the dry spell will become significantly longer in the Northwest, along the southern border, and in the central US. The bias-corrected NA-CORDEX projects significantly extended dry spells over greater areas in the southern US compared to the other two datasets. However, the response of dry spell length to 0.5°C less warming varies spatially, and models show less agreement within and among the datasets in most of the regions (shown as not robust in Figures 7d-f). Only over the West, the dry spell is significantly reduced, by approximately three days, with 0.5°C less warming.

The projected changes in drought frequency are shown in Figures 7g-i, which exhibits similar spatial patterns as the dry spell changes. Under the 2.0°C global warming, drought events become fewer in the majority of the northern US due to the increased precipitation (Figure 6), and droughts become more frequent over the West and Southwest. The three datasets agree on the general locations of the increased drought events, but CMIP5 shows the smallest changes and the bias-corrected NA-CORDEX shows the strongest increase. For instance, the bias-corrected NA-CORDEX indicates that drought frequency would increase by over 20% in the Southwest, which accounts for more than two months with SPI below -0.8 every year, while the increased drought based on CMIP5 is just over one month. The difference between CMIP5 and bias-corrected NA-CORDEX implies downscaling and bias correction can significantly influence the simulated precipitation variability over those regions (also shown in Figure 6), and its mechanism needs to be further investigated in future studies. With 0.5°C less global warming, robust reductions in drought frequency are only found in limited areas of the Southwest. The drying trend in the western US under a warming climate is also found in previous studies (Zhao and Dai 2017; Naumann et al. 2018). This can be associated with the wet-get-wetter and dry-get-drier pattern or the thermodynamic contribution of global warming (Chou et al. 2013). The drying can also be associated with mean zonal moisture advection due to seasonally dependent changes in land-sea moisture contrast over the west US under warming (Dong et al. 2019). Therefore, less warming can potentially reduce the dry spells over these regions. The changes in CDD and SPI suggest there are likely increased risks posed by meteorological drought in the western and southwestern US under a warming climate, resulting in substantial impacts on the ecosystems, agriculture, and energy infrastructure. Although the reduced drought hazard by limiting global warming to 1.5°C is only found in very limited areas, considering the elevated water demand induced by global temperature increases (Wang et al. 2016), the 0.5°C less warming can still potentially reduce water stress of the natural and agricultural environment.

3.3 Regional Variability

Figure 8 summarizes the influence of 0.5°C less warming on all the temperature indices in the nine climate regions. We use boxplots to demonstrate the robustness of their changes in individual regions. The three datasets generally agree on the significant changes in the four temperature indices over all the regions, but there is an inter-model spread within each dataset. Regionally, there are greater changes in TX90p in Ohio Valley, Southwest, South, and Southeast, and greater changes in TNn in the northern US (including Northwest, Northern Rockies and Plains, Northeast, Upper Midwest, and Ohio Valley).

Compared to the temperature extremes, the changes in precipitation exhibit less robustness and greater inter-model spread (Figure 9). This result is consistent with the IPCC report and other modeling studies (Sillmann et al. 2013). Decreased Rx5day is found in Northwest, Northern Rockies and Plains, Upper Midwest, and Ohio Valley. There is a robust decrease in Rx10mm in the Northwest, Northern Rockies, and Plains, and a robust decline in CDD only in the West. Uncertainties in the estimated changes exist in other regions. For instance, CMIP5 and the raw NA-CORDEX agree on the reduced drought length in the Ohio Valley with 0.5°C less warming, but more than half of bias-corrected NA-CORDEX models show an opposite change. Furthermore, no robust changes are found in drought frequency over the nine regions. As shown in Figures 7j-l, significant influence of the 0.5°C less warming on drought frequency only appears in some areas of California and Arizona, and does not remain in the regional averages.

To better illustrate how future intensification of climate extremes can be avoided by 0.5°C less warming, we use Equation 1 to quantify the avoided intensification relative to changes under the 2.0°C global warming (Table 3). The actual values in avoided change are shown in Table S1. If future warming is limited from 2.0°C to 1.5°C, the projected intensification in hot extremes will be reduced by 32~46% in intensity and 35~42% in frequency across the country. The changes in the intensity of heavy precipitation can also be significantly limited by 23~41% in regions such as the North, South, and Southeast. However, impacts on the frequency of heavy precipitation and drought duration are only evident in limited areas. For instance, under the 2.0°C global warming, there is more frequent heavy precipitation in the Northwest and prolonged dry spell in the West (Figure 7). The 0.5°C less warming would limit the intensification of these hazards by 28% and 35%, respectively.

3.4 Seasonal Variability

Additionally, considering the seasonality of trends in precipitation, we examine the changes in Rx5day in different seasons (Figure 10). Under the 2.0°C warming, all the datasets suggest a robust increase in Rx5day in most areas of the contiguous US during winter and spring except for some regions in the Southwest and South. This is consistent with the annual changes in Rx5day (Figure 6 a-c). During summer and fall, CMIP5 shows increased Rx5day in the eastern US and parts of the western US, and no evident change is found in the central US. NA-CORDEX partially agrees with CMIP5. However, in biased-corrected NA-CORDEX, there is a robust decrease in Rx5day in the South.

With the 0.5˚C less warming, all the datasets show that the increased Rx5day during winter and spring can be greatly avoided in the northern and central US (Figure S2). This spatial pattern is consistent with the changes at the annual scale (Figure 6d-f). This suggests the projected (or avoided) changes in annual heavy precipitation intensity are more contributed by winter and spring. Similar seasonal contributions are also found in R10mm (not shown). The greater increase in winter/spring extreme precipitation can be explained by Clausius–Clapeyron relationship, in which changes in extreme precipitation are largely determined by increases in temperature (Wehner 2013), or the thermodynamic contribution to winter extratropical cyclones (Akinsanola et al. 2020; Yettella and Kay 2017). The seasonal contributions agree with previous studies on seasonal changes in extreme precipitation events (Wehner 2013; Singh et al. 2013; Janssen et al. 2016; Ning et al. 2015; Akinsanola et al. 2020). As wet extremes in spring can harm agricultural production through delayed and extended planting periods (Urban et al. 2015), the avoided increase in wet extremes would exert positive impacts on agriculture in the northern and central US. Concurrently, reductions in extreme precipitation has tangible effects on the frequency and intensity of flash flooding and riverine flooding in both urban and rural areas.

4. Discussion And Conclusion

Based on three climate datasets (CMIP5, raw NA-CORDEX, and bias-corrected NA-CORDEX), this study evaluates the changes in eight temperature and precipitation indices under a warming climate and the potential influence of 0.5°C less warming in the contiguous US. Under warming of 2.0°C, heat extremes will become more intense and more frequent across the country; heavy precipitation will be more intense and more frequent in large areas of the northern US; and drought will get longer in some regions of the southern US and the Midwest. With 0.5°C less warming, the risks of extreme events (such as heatwave, flood, and drought) can be limited in many regions of the country.

4.1 Reductions in Climate Change Impacts with Less Warming

For the changes in precipitation, it is hypothesized that precipitation intensities are expected to increase at scaling rates about 7% per degree warming according to the Clausius-Clapeyron relationship (Trenberth et al. 2003), and the rate of increase for heavy precipitation can even exceed 7% because the additional latent heat released from the increased water vapor could invigorate the storms (Trenberth et al. 2003). Meanwhile, in a warmer climate, it would take longer for evaporation to replenish atmospheric moisture, leading to longer dry spells between storms (Shiu et al. 2012). More investigations are needed for the mechanism of the projected regional wet and dry extremes in future work.

Consistent with previous assessment (Hoegh-Guldberg et al. 2018), our results also show that constraining global warming to 1.5°C would reduce the risks of hot extremes, heavy precipitation, and drought regionally. Because the extreme events would have profound impacts on human societies and ecosystems, the avoided intensification identified in this study suggests the social and ecological benefits of 0.5°C less warming. For instance, the Great Lakes would be one of the regions with the earliest emergence of anthropogenically forced heat waves across the country (Lopez et al. 2018). The 0.5°C less warming can significantly reduce the intensity and frequency of heatwaves, and limit the risk they pose to the aquatic ecosystem and urban populations (Wuebbles et al. 2010). Another important implication is drought in the western US, where there are robust projections of increased drought frequency and severity. The 0.5°C less warming would significantly reduce dry spell and drought frequency, thus lowering the risk of climate change to agriculture in this region. Considering the complexity of droughts, the changes in other features of droughts (such as seasonality, duration, and severity) need further investigation in future studies.

4.2 Comparison of GCMs and RCMs

Another aspect of this assessment is to examine the consistency of the detected changes between GCMs (CMIP5) and RCMs (NA-CORDEX), and between the raw downscaling and bias-corrected downscaling. The three datasets used in this study show a generally good agreement in the detected changes. Compared to CMIP5, results from NA-CORDEX present more spatial variations due to the high spatial resolution. The projected changes in NA-CORDEX are more intense, especially for precipitation indices in some regions (Figures 6-7), implying possible added values of regional climate downscaling (Di Luca et al. 2012). Figure 11 presents an example of the avoided changes in heat extreme frequency and heavy precipitation in a GCM (GFDL-ESM2M) and the corresponding RCM (WRF downscaling GFDL-ESM2M with and without bias correction). Compared to the GCM that provides the lateral boundary conditions, the spatial pattern of the detected changes remains in the RCM to some extent, but the magnitude of the changes is amplified.

We also noted considerable differences between the raw and bias-corrected RCM downscaling. The raw projections show an evident increase in TXx in the Midwest, while the bias-corrected projections show a slight cooling and lead to greater changes in TXx with the 0.5°C less global warming, implying the added value of bias correction. This discrepancy can be attributed to the bias of climate models in representing the observed cooling trend in the central US (Pan et al. 2013), which can be associated with North Atlantic multidecadal oscillations (AMO) and local/regional land surface processes (Kumar et al. 2013; Pan et al. 2013). For the drought indices, bias corrections show greater changes in CDD and SPI-based frequency over the western and southern US. Because the bias correction algorithm constrains future climate projections using observations, it is necessary to consider bias corrections in the assessment of projected climate changes (Peng et al. 2019).

We also examine the changes in temperature and precipitation extremes using the NA-CORDEX simulations at the 25-km resolution (Figures S3-S4). Overall, the 25-km results show a very consistent pattern and magnitude of the changes in temperature and precipitation indices compared to the NA-CORDEX at the 50-km resolution (Figures 3-7). Meanwhile, we noted that the 25-km results show more details of the changes in heavy precipitation frequency, such as an evident decrease in R10mm over the mountainous regions of the western US, which does not appear in the 50-km results, implying that a higher spatial resolution may offer new insights in simulated precipitation extremes. This resolution effect is also confirmed in other CORDEX studies (e.g., Mahoney et al. 2021), which suggest that model resolution does not systematically impact the seasonal cycle of precipitation in the western US, but greater intensity of precipitation extremes is found over complex and elevated terrain in the higher-resolution simulation.

4.3 Limitations

Besides the disagreement between the CMIP5 and NA-CORDEX datasets, it should also be noted that uncertainties exist among different models, downscaling methods (and their training datasets), and within model runs (internal variability). Although all climate models project robust changes in temperature extremes between the 1.5°C and 2°C global warming, there is low confidence in the changes in precipitation, and robust changes are only revealed in limited areas (such as, Northwest, Northern Rockies, and Plains for heavy precipitation intensity and extremes in Figure 9). The inter-model spread not only exists among the different GCMs, but also remains among the different RCMs even with the same boundary conditions (not shown). This issue is also discussed in previous studies (Kharin et al. 2013; Hoegh-Guldberg et al. 2018), which have reported the large uncertainties in the precipitation extremes due to natural variability and model deficiencies in relevant physical processes (Fischer et al.

2013; Pfahl et al. 2017). Moreover, the robustness of climate projections in this study is based on the models' agreement on the sign of changes. The same approach has been used in previous studies (such as, Hoegh-Guldberg et al. 2018; Nikulin et al. 2018; Peng et al. 2019; Sillmann et al. 2017; Zhang et al. 2018). However, it should be noted that the agreement on the sign does not necessarily mean the projected changes are statistically significant in those models. This is especially true for precipitation extremes. The changes in precipitation extremes (e.g., Rx5day and R10mm) are not statistically significant in several models, although over 75% of the models agree on the precipitation changes (not shown). Therefore, precipitation projections need more process-based assessments in our future studies (Thibeault and Seth 2015).

Another limitation of the study is the approach to identify the 1.5°C and 2°C global warming, which is calculated by sampling at the time of global temperature increments. This approach assumes the implications of global temperature increments will be the same regardless of the emission pathway (James et al. 2017). However, using the same approach, previous studies found that the identified 0.5°C less warming in RCP8.5 and RCP4.5 may have different effects on regional climate extremes (Peng et al. 2019) and moisture fluxes (Tamoffo et al. 2019). Due to the limited number of the RCP4.5 projections in NA-CORDEX (only five GCM-RCM combinations are available), it is difficult to provide a fair comparison in multimodel ensembles between the two emission scenarios. However, we note evident differences even by comparing individual models. Figure S5 presents an example of the avoided changes in heavy precipitation events between RCP4.5 and RCP8.5 in a GCM (CanESM2) and a corresponding RCM (CanRCM4). The timing of the 1.5°C and 2°C global warming in RCP4.5 is 2017 and 2031, respectively, while the years in RCP8.5 are 2016 and 2026. In this case, the avoided heavy precipitation is greater than that in the RCP8.5 scenario. Assuming there is a similar "warming" background within the identified time window between RCP8.5 and RCP4.5, the different responses in climate extremes can also be a result of other factors, such as aerosols and land use (Riahi et al. 2011; Thomson et al. 2011). Table S2 compares the avoided changes based on the RCP4.5 and RCP8.5 projections in CMIP5, which show similar changes in the temperature indices. The RCP8.5 has a slightly greater avoided change in Rx5day, and both scenarios do not show robust changes in other precipitation extreme indices. Although this discrepancy may provide further insight into climate change mitigation in terms of how climate extremes respond to greenhouse gas reduction, more complete downscaling projections are needed for a robust assessment of the regional difference between different emission scenarios in our future work.

4.4 Summary

This study investigates projected changes in temperature and precipitation extremes over the contiguous US using both GCM and RCM projections. Future warming coincides with more frequent heat extremes and increased intensity of hot days, more severe heavy precipitation, longer dry spells, and more frequent drought events. Based on the difference between the 2.0°C and 1.5°C warming targets in three climate datasets, we highlight the regions that can significantly benefit from the 0.5°C less global warming: 1) reduced severity and frequency in heat extremes across the contiguous US; 2) reduced intensity of heavy precipitation in the Northwest, Northern Rockies and Plains, Upper Midwest, and Ohio Valley; 3) reduced frequency of heavy precipitation in the Northwest, Northern Rockies and Plains; and 4) reduced dry spell and drought frequency in some regions of the West. Although uncertainties still exist among climate models and emission scenarios, our results suggest that a low warming target is necessary for reducing the risk of certain extreme hazards across the country.

Declarations

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Availability of data and material: All the NA-CORDEX data are obtained from the NCAR Climate Data Gateway (https://www.earthsystemgrid.org/search/cordexsearch.html). CMIP5 data are downloaded through the ESGF@DOE/LLNL node (https://esgf-node.llnl.gov/search/cmip5/).

Code availability: Data analysis is performed using NCAR Command Language (NCL). NCL codes are available from the corresponding author upon reasonable request.

Authors' contributions: L.C. designed the study and performed data analysis. All authors contributed to the writing and revising of the paper.

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Tables

Table 1. List of 13 NA-CORDEX GCM-RCM combinations used in this study.

Model combination	RCM	GCM	Available resolutions
1	CanRCM4	CanESM2	50 km, 25 km
2	CRCM5-UQAM	CanESM2	50 km, 25 km
3	CRCM5-UQAM	MPI-ESM-LR	50 km
4	CRCM5-UQAM	MPI-ESM-MR	50 km, 25 km
5	HIRHAM5	EC-EARTH	50 km
6	RCA4	CanESM2	50 km
7	RCA4	EC-EARTH	50 km
8	RegCM4	GFDL-ESM2M	50 km, 25 km
9	RegCM4	HadGEM2-ES	50 km, 25 km
10	RegCM4	MPI-ESM-LR	50 km, 25 km
11	WRF	GFDL-ESM2M	50 km, 25 km
12	WRF	HadGEM2-ES	50 km, 25 km
13	WRF	MPI-ESM-LR	50 km, 25 km

Table 2. Definition of eight climate indices used in this study. Details of the first seven indices can be found at Climdex (https://www.climdex.org/learn/indices/).

Climate index	Definition	Unit
TXx	Annual maxima of daily maximum temperature	K
TNn	Annual minima of daily minimum temperature	K
TX90p	Percentage of days when daily maximum temperature > 90th percentile	%
TN10p	Percentage of days when daily minimum temperature < 10th percentile	%
Rx5day	Annual/seasonal maximum consecutive 5-day precipitation	mm
R10mm	Annual/seasonal count of days when daily precipitation ≥ 10mm	days
CDD	Annual maximum number of consecutive days with daily precipitation < 1mm	days
drought frequency	Percentage of months when standardized precipitation index < -0.8	%

Table 3. Avoided intensification (in %) of climate extremes in nine climate regions of the US. The values

are ensemble medians of all CMIP5 and NA-CORDEX models. Bold indicates that more than 75% of the models agree on the sign of the change. Shading of the table cell indicates the magnitude of the change.

	1. NW	2. NP	3. NE	4. MD	5. OV	6. WS	7. SW	8. ST	9. SE
TXx	**-36.0**	**-36.7**	**-39.2**	**-41.0**	**-46.2**	**-33.8**	**-31.8**	**-39.5**	**-43.7**
TX90p	**-35.1**	**-36.7**	**-41.6**	**-40.3**	**-40.0**	**-35.3**	**-36.2**	**-38.9**	**-39.7**
TNn	**-42.5**	**-42.5**	**-42.0**	**-40.5**	**-44.5**	**-32.3**	**-35.1**	**-40.4**	**-38.4**
TN10p	**-31.0**	**-33.6**	**-35.1**	**-35.2**	**-37.1**	**-31.0**	**-32.1**	**-37.2**	**-39.0**
Rx5day	**-40.8**	**-41.3**	**-23.3**	**-36.6**	**-37.7**	-22.6	-25.6	**-37.3**	**-36.6**
R10mm	**-28.3**	**-37.6**	-5.5	**-27.8**	-17.3	-61.1	-30.0	-26.3	-4.8
CDD	**-25.0**	-49.2	-31.9	-24.3	-29.8	**-34.7**	-63.7	-19.4	-22.2
drought frequency	**-24.9**	-37.9	-18.5	-18.9	-6.3	-26.2	-40.3	-16.8	-6.2