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Increasing population exposure to global warm-season concurrent dry and hot extremes under different warming levels

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Abstract

Projecting future changes in concurrent dry and hot extremes (CDHEs) and the subsequent socio-economic risks (e.g. population exposure) is critical for climate adaptation and water management under different warming targets. However, to date, this aspect remains poorly understood on both global and regional scales. In this study, the changes in future CDHEs and their population exposures under 1.5 ◦C, 2 ◦C, and 3 ◦C warming were quantified using a Standardized Dry and Hot Index calculated based on the newly released Coupled Model Intercomparison Project Phase 6 climate model outputs and global population datasets. It was found that relative to the baseline period (1986–2005), the severity of CDHEs would increase on the global scale and in most regions, such as in Southern Europe, the Mediterranean, Sahara, West Africa, Central America, Mexico, the Amazon, and the west coast of South America under 1.5 ◦C, 2 ◦C, and 3 ◦C of warming. Stabilizing the warming at 1.5 ◦C would constrain the adverse influence of CDHEs on the population suffering from severe CDHEs in most regions (especially in Central Europe, Southern Europe, the Mediterranean, Eastern North America, West Asia, East Asia, and Southeast Asia). Globally, the population impacted by severe CDHEs (with a constant 2000 population) would increase by 108 and 266 million (149 and 367 million when constant 2080 population is applied) for 2 ◦C and 3 ◦C increase compared to a 1.5 ◦C increase. These findings provide scientific evidence of the benefit of limiting anthropogenic warming to 1.5 ◦C in terms of the socio-economic risks related to CDHEs.

1. Introduction

The frequency and severity of droughts and heat waves have been demonstrated to increase under global warming (Trenberth et al. 2014; Seneviratne et al. 2014, AghaKouchak et al. 2015, Huang et al. 2017, Baldwin et al. 2019, Zhang et al. 2019, Shiogama et al. 2020, Li et al. 2021), having devastating impacts on regional water availability, agriculture, ecosystems and human health (Zipper et al. 2016, Liu et al. 2018a, Chen and Sun 2019, Coffel et al. 2019, Russo et al. 2019, Liu and Sun 2019a, Liu et al. 2019b). The co-occurrence of drought and hot events, commonly referred to as concurrent dry and hot extremes (CDHEs), has received increased attentions during recent decades due to the growing awareness of their amplified consequences compared to any individual events (Mazdiyasni and AghaKouchak 2015, Zscheischler and Seneviratne 2017, Hao et al. 2018, 2020, Feng et al. 2021). During CDHEs, heat stress
and lack of available freshwater often have large negative impacts on human society (commonly assessed based on population exposure), including human health and even deaths (Raymond et al. 2020, Zscheischler et al. 2020). For example, the events caused by a precipitation deficit and record-breaking temperatures in the summers of 2003, 2010 and 2015 in western-central Europe resulted in numerous heat-related deaths (Ionića et al. 2017). In the summer of 2010, Russia was struck by an unprecedented heatwave associated with below-normal precipitation in the first seven months of the year, which led to approximately 55,000 deaths (Barriopedro et al. 2011). As climate change modifies precipitation patterns and increases temperatures, quantifying the variations in CDHEs and their subsequent population exposure will be critical to sustaining regional development and mitigating the negative effects of climate change.

To facilitate global climate governance, the Paris Agreement, struck in 2015, called on the scientific community to make a new form of contributions to support the Intergovernmental Panel on Climate Change (IPCC) Special Report on the impacts of 1.5 °C global warming (Diffenbaugh et al. 2018). Thus, a great deal of scientific research has been conducted to inform climate policy makers about potential climate risks and benefits under different warming targets (e.g. 1.5 °C, 2.0 °C and greater; IPCC Special Report 2018). For example, focusing on droughts and heat waves in isolation, several studies (Lehner et al. 2017, Liu et al. 2018b, Gu et al. 2020) have projected changes in global droughts and/or their socioeconomic exposures and found that limiting global warming to 1.5 °C instead of 2 °C can perceptibly mitigate the negative impacts of drought over most of the world’s land area. Other studies (Dosio et al. 2018, Russo et al. 2019, Yang et al. 2020) have found that the risk (e.g. population exposure) of heat waves would also be significantly reduced at both the global and regional scales if global warming was limited to <1.5 °C. However, due to the amplified influences of CDHEs compared to those arising from one extreme alone, ignoring their concurrences may result in an underestimation of the adverse impacts on human society under different warming levels (Zscheischler et al. 2018).

By considering the impacts of dry and hot events simultaneously, based on Coupled Model Intercomparison Project Phase 5 (CMIP5) Global Climate Models (GCMs). It has been shown that overall, the risk posed to human health in China (particularly in eastern regions) by CDHEs under 1.5 °C and 2 °C warming would increase (Wu et al. 2021). However, currently, changes in CDHEs and their population exposures under different warming levels remain poorly understood at both the global and regional scales, especially in regions with low adaptive capacities and rapid population growth, which may face distinct stress during adverse climate extremes even under the same global warming level (Diffenbaugh and Burke 2019). The objective of this study is to project future changes in CDHEs and their population exposures under 1.5 °C, 2 °C and 3 °C global warming on both the global and regional scales using a suite of the latest CMIP6 climate models. The rest of this paper is organized as follows. Section 2 describes the Climatic Research Unit (CRU) data, the GCM outputs and the Shared Socioeconomic Pathway Scenarios (SSPs) population data. The calculation of the Standardized Dry and Hot Index (SDHI) and the definition of the different global warming levels are also introduced. The results and discussion are presented in sections 3 and 4, and the conclusions are presented in section 5.

2. Data and methodology
2.1. Data
The monthly air temperature (T) and precipitation (P) outputs during 1850–2100 from 13 CMIP6 climate models (see table 1) under the SSP5-8.5 scenario were used, which can be downloaded from the Earth System Grid Federation (ESGF) node at the Lawrence Livermore National Laboratory (LLNL, https://esgf-node.llnl.gov/search/cmip6/). Whilst a large number of climate models and SSP scenarios are available in the CMIP6 archive, those that fully satisfied our data requirements (i.e. monthly T and P are available from 1850 to 2100 under SSP5-8.5) were used to quantify the CDHEs and to composite different warming levels (e.g. 1.5 °C, 2 °C, 3 °C and greater). Moreover, the monthly T and P from the Climatic Research Unit (CRU TS v.4.04, https://catalogue.ceda.ac.uk/uyuid/89e1e34ec3554dc9859a573262bce9; Harries et al. 2020) were also used to verify if the CDHEs can be reflected reasonably through an ensemble of multiple GCMs.

To consider the population affected by CDHEs, the Global One-Eighth Degree Population Base Year and Projection Grids Based on the SSPs, v1.01 (Jones and O’Neill 2016, 2020; link: 10.7927/m30p-j498) were used, which comprises the spatially explicit global population for base year 2000 and population projections for 2010–2100 (20 year steps) and is consistent with the new SSPs at a spatial resolution of 0.125°. The scenario-based population projections were downscaled using a gravity-type model calibrated using historical data to reflect the spatial (change) distributions prescribed by the baseline population and each SSP, which enables the population in the baseline and future periods to communicate efficiently and to be better applied to the assessment of the exposure/vulnerability to hazards (Jones and O’Neill 2016). In this study, SSP5, which describes a fossil-fuel development pathway with large socio-economic challenges in mitigation and coincides with the SSP 5-8.5 ScenariosMIP
Table 1. Details of the CMIP6 climate models used in this study.

| Climate models       | Institution ID | Nominal resolution |
|----------------------|----------------|--------------------|
| ACCESS-ESM1-5        | CSIRO          | 250 km             |
| BCC-CSM2-MR          | BCC            | 100 km             |
| CanESM5              | CCCma          | 500 km             |
| CESM2-WACCM          | NCAR           | 100 km             |
| EC-Earth3-Veg        | EC-Earth-Consortium | 100 km |
| FGOALS-f3-L          | CAS            | 100 km             |
| GFDL-ESM4            | NOAA-GFDL      | 100 km             |
| INM-CM5-0            | INM            | 100 km             |
| IPSL-CM6A-LR         | IPSL           | 250 km             |
| KACE-1-0G            | NIMS-KMA       | 250 km             |
| MIROC6               | MIROC          | 250 km             |
| NorESM2-MM           | NCC            | 100 km             |

(Scenario Model Intercomparison Project) experiment, was applied. In addition, 26 sub-regions (IPCC Special Report 2012) were used to interpret the results on sub-continental scales. All of the above datasets were uniformly re-gridded to a regular 1.5° latitude-longitude grid through bilinear interpolation.

2.2. Methods

2.2.1. Definition of 1.5 °C, 2 °C, and 3 °C warming The baseline, 1.5 °C, 2 °C and 3 °C warming levels were defined based on the method adopted by Schleussner et al (2016). First, the global mean temperature (GMT) weighted by \( \sqrt{\cos(\text{Latitude})} \) was computed to consider the dependence of the grid density on latitude (Liu et al 2018b) during 1850–2100 for each climate model. The multi-model ensemble (MME, 13 climate models) mean GMT was calculated and smoothed based on a 20 year moving window. Following the methods of Schleussner et al (2016) and Wang et al (2017), the commonly used 1986–2005 period was selected as the baseline period when the observed GMT was about 0.6 °C warmer (whilst the MME GMT was 0.4 °C–0.7 °C warmer) than the preindustrial period (1850–1900). This translates to warming of 0.9 °C (2023–2042 under the SSP5-8.5), 1.4 °C (2037–2056 under the SSP5-8.5), and 2.4 °C (2061–2080 under the SSP5-8.5) above the baseline period for the 1.5 °C, 2 °C and 3 °C warming scenarios, respectively.

2.2.2. Characterize CDHEs and their population exposures There are two main types of approaches to quantifying CDHEs. One type defines the CDHEs using varied thresholds for the period of interest, which enables the detection of changes in the occurrence of CDHEs but fails to distinguish their severity levels (Hao et al 2013, Mazdiyasni and AghaKouchak 2015). To overcome this limitation, several joint indicators of multiple extremes such as the Climate Extremes Index (Gallant et al 2014), the SDHI (Hao et al 2018), and the Standardized Compound Event Indicator (Hao et al 2019) have been proposed. In this study, the SDHI (the smaller the SDHI value, the more severe the CDHEs) is used to evaluate the severity of the CDHEs due to its relatively simple and effective nature at the global scale. Specifically, first a matrix, \( X = G_1 \mathcal{P}/G_2 \mathcal{T} \) (\( G_1 \mathcal{P} \) and \( G_2 \mathcal{T} \) are the marginal probability distribution functions for precipitation and air temperature, respectively), was defined to incorporate the comparative status of both the heat and moisture conditions, where a lower \( X \) means a low ratio of the precipitation percentile to the temperature percentile compared with the background climatology and more severe CDHE conditions (Hao et al 2018). Then, \( X \) was fit with a marginal cumulative distribution function \( F \) and \( F(X) \) was standardized using the standard normal distribution \( \Phi \) (SDHI = \( \Phi^{-1} [F(X)] \)), following the concepts of the standardized precipitation index (SPI; McKee et al 1993) and the standardized precipitation evapotranspiration index (Vicente-Serrano et al 2010). Following the method of Hao et al (2018), the Gringorten plotting position formula (i.e. \( P = (i-0.44)/(n+0.12) \), where \( n \) is the length of the data and \( i \) is the rank) was used to compute the marginal distributions of \( G_1, G_2 \) and \( F \) (Gringorten 1962). Because CDHEs usually occur in the warmer months, this study focused on the warm season, which is defined as the climatologically hottest three-month period in each land grid (Zscheischler and Seneviratne 2017).

The severity of the CDHEs can be further categorized using different SDHI thresholds, for example, \(-0.5, -0.8, -1.3, -1.6 \) and \(-2.0 \), from the least intense to exceptional CDHEs (Hao et al 2018). For each GCM per period (i.e. the baseline and the 1.5 °C, 2 °C and 3 °C warming scenarios), the population affected by severe CDHEs (SDHI < -1.3) per grid-cell was calculated as the population times the frequency of severe CDHEs during the corresponding 20 years. To avoid any artifacts that arise from the convolutions of the climate and population dynamics, the severe CDHE population exposures of the baseline, 1.5 °C, 2 °C and 3 °C warming levels were compared using the fixed 2000 (pop2000) and SSP5 2080 (pop2080) population counts (i.e. by imposing severe CDHEs at the global warming levels on today’s society and on that near the end of this century, respectively).

3. Results

3.1. Global SDHI and severe CDHE population exposure in baseline period To verify the abilities of the multiple climate models to reflect the SDHIs and severe (SDHI < -1.3) CDHE population exposures, their geographic distributions were compared with against those estimated from the CRU data (observations) during the baseline period (1986–2005). Overall, the large-scale features of the GCM-calculated SDHI are close to those calculated from the observations, with relatively more (less) severe CDHEs in the Sahara, Southeast Asia, Central
Figure 1. Global spatial patterns of the SDHI ((a) and (c)) and population exposure (million, (b) and (d)) to severe CDHEs (SDHI < −1.3) during the baseline period (1986–2005). The SDHIs were calculated from (a) the multi-model ensemble median of 13 climate models and (c) the CRU data, respectively. The population exposures were estimated based on the constant population count in 2000. The legend in (a) applies to (c); the legend in (b) applies to (d).

America, Mexico, the Amazon, northeastern Brazil, and the west coast of South America (Northern Asia, southeastern South America, and Northern Europe), but the estimated magnitudes of both the positive and negative SDHIs are attenuated in most of the regions (figures 1(a) and (c)). Moreover, the spatial patterns of the severe CDHE population exposure estimated using the CRU and GCM calculated SDHIs (with the constant 2000 population count; ∼500 million people were exposed to severe CDHEs at the global scale from 1986 to 2005) are also quite close, with relatively higher exposures in densely populated regions such as China, India, Nigeria, eastern North America, Mexico, and Central Europe.

3.2. Changes in the severity of CDHEs under different warming levels

The changes in the severity of CDHEs (represented by the SDHI) were projected on both the global and sub-continental scales under different warming levels (figure 2). The severity of the CDHES increased on the global scale (SDHI decreases by −0.6, −0.9, and −1.2), and in most regions, especially in Southern Europe and the Mediterranean (SDHI decreases by −0.7, −1.3, and −1.7), the Sahara (SDHI decreases by −0.8, −1.1, and −1.5), West Africa (SDHI decreases by −0.5, −0.8, and −1.2), Central America and Mexico (SDHI decreases by −0.8, −1.1, and −1.5), the Amazon (SDHI decreases by −0.8, −1.1, and −1.6), and the west coast of South America (SDHI decreases by −0.9, −1.1, and −1.5) under 1.5 °C, 2 °C and 3 °C warming, respectively, compared with the baseline period. Interestingly, the severity of the CDHES increase in Northern Australia (SDHI decreases by −0.7 and −0.9) and Southeast Asia (SDHI decreases by −0.9 and −1.2) under 1.5 °C and 2 °C warming, but reverse is seen (SDHIs equal to −0.8 and −1.0 in Northern Australia and Southeast Asia, respectively) under 3 °C warming. The Wilcoxon Sign Test (hatching in figures 2(a)–(c)) shows that the projected changes in the MME median SDHI under different warming levels are statistically robust over the Earth’s landmass, except for the Sahara.

The changes in the frequency of severe CDHES (SDHI < −1.3) with anthropogenic warming were also projected. Compared with the baseline period, the frequency of severe CDHES increases gradually under 1.5 °C, 2 °C and 3 °C warming at the global scale and in most regions, except for West Africa (decreases by 1% under 1.5 °C warming and then increases by 1% and 7% under 2 °C and 3 °C warming), East Africa (decreases by 0.5% under 1.5 °C warming and then increases by 0.6% and 2% under 2 °C and 3 °C warming), South Asia (decreases by 0.3% under 1.5 °C warming and then increases by 3% and 4% under 2 °C and 3 °C warming), and Northern Europe (increases by 3%, 4%, and 4% under 1.5 °C, 2 °C and 3 °C warming).

3.3. Changes in severe CDHE population exposure

Considering the CDHE is becoming especially severe in regions that are already water-short, we need to better assess its socio-economic risks (e.g. population exposure, water scarcity and agricultural productions) to support climate change mitigation under different warming levels. To calculate the population affected by severe CDHES (SDHI < −1.3), we first reconcile the SDHI projection with the pop2000 (figure 3). The severe CDHE population exposure increases by 93, 201, and 359 million on the global scale under 1.5 °C, 2 °C and 3 °C warming. Specifically, more population is exposed to severe CDHES in East Asia (34, 55, and 89 million), Central Europe (11, 12, and 29 million), Southeast Asia (11, 17, and 29 million), South Europe and the Mediterranean (7,
Figure 2. Changes in the multi-model ensemble median SDHI on the (a)–(c) global and (d)–(f) regional scales from the baseline period to 1.5 °C, 2 °C, and 3 °C warming. The sub-continental regions adopted by the IPCC (2012) are shown in (g). The legend in (a) applies to (b) and (c). The hatching in (a)–(c) indicates changes that are significant according to the Wilcoxon Sign Test (95% confidence). The colors in (d)–(f) show the multi-model maximum (red), multi-model minimum (blue), and multi-model ensemble median (the dividing line between the blue and red colors).

Figure 3. Changes in population exposure (million) to severe CDHEs (SDHI < −1.3) from the baseline period to 1.5 °C, 2 °C, and 3 °C warming. The population exposures were estimated based on the fixed (a)–(c) 2000 and (d)–(f) SSP5 2080 population counts. The legend in (a) applies to (b)–(f). The hatching indicates the changes that are significant according to the Wilcoxon Sign Test (95% confidence).

15, and 32 million), West Asia (4, 8, and 14 million), eastern North America (4, 7, and 10 million), Central Asia (3, 7, and 11 million), Central America and Mexico (3, 6, and 14 million), central North America (3, 5, and 6 million), western North America (3, 4, and 6 million), South Africa (2, 5, and 9 million), southeastern South America (2, 5, and 6 million), North Asia (2, 3, and 5 million), the Tibetan Plateau (2, 5, and 4 million), the Sahara (1, 2, and 4 million), the Amazon (1, 3, and 5 million), northeastern Brazil (1, 3, and 5 million), the west coast of South America (1, 2, and 4 million), southern Australia
and New Zealand (0.4, 0.7, and 1 million), Northern Australia (0.07, 0.11, and 0.19 million), Eastern Canada, Greenland, and Iceland (0.01, 0.02, and 0.02 million), and Alaska and Northwestern Canada (0.008, 0.01, and 0.02) under 1.5 °C, 2 °C and 3 °C warming, respectively.

Although this study focused on assessing the effects (i.e. the changes in the CDHEs and their population exposures) of additional warming, the use of the pop2000 and pop2080 also allowed for the investigation of the role regional population growth plays in severe CDHE population exposure. When the pop2080 was applied, the severe CDHE population exposure increased further on the global scale (106, 255, and 473 million) under 1.5 °C, 2 °C, and 3 °C warming, respectively, and in most regions such as Central Europe, Southeast Asia, Southern Europe, the Mediterranean, West Asia, eastern North America, and Central Asia. However, since the pop2080 is lower than the pop2000, the severe CDHE population exposures are relatively less when the pop2080 is applied in East Asia (25, 41, and 66 million), North Asia (2, 3, and 5 million), the Tibetan Plateau (2, 2, and 3 million), northeastern Brazil (1, 3, and 5 million), and the west coast of South America (1, 2, and 4 million) under 1.5 °C, 2 °C, and 3 °C warming, respectively (figure 4).

4. Discussion

4.1. Comparison with existing studies

The changes in the CDHE hotspot regions and their population exposures identified in this study are consistent with the results of recent global and regions studies overall (Hao et al 2018, Manning et al 2019, Alizadeh et al 2020, Hao et al 2020, De Luca et al 2020, Wu et al 2020, Feng et al 2021), despite the different approaches and datasets used (the study periods may be different). For example, CDHEs have been projected to increase with global warming in India (Mishra et al 2020), China (Lu et al 2018), the Nile Basin (Coffel et al 2019), and Africa (Weber et al 2020) driven by a strong coupling during hot and dry days, which all support the findings of this study. The obvious increases in future CDHEs in the Amazon, the west coast of South America, Central America, Mexico, and Southern Europe, and the Mediterranean under 1.5 °C, 2 °C, and 3 °C warming are also consistent with the increased risks of droughts and water shortages projected in these regions (Liu et al 2018a, 2018b). The CDHE population exposure in Africa projected in this study coincides with the results of Weber et al (2020), who by analyzing population exposures to coincident heat waves and droughts projected a strong increase in exposure in Africa (especially for West Africa: 2.2 billion person-events, Central-East Africa: 1.7 billion person-events, and Northeast Africa: 1.0 billion person-events) under the RCP8.5/SSP3 scenario.

4.2. Regional drivers of increasing CDHEs

It has been demonstrated that the strengthening of the dependences between precipitation and temperature would exacerbate the increase in the CDHEs in many regions of the world (Zscheischler and Seneviratne 2017). Thus, the actual drivers of the regional changes in the SDHI were analyzed by projecting the changes in the warm-season precipitation and temperature under 1.5 °C, 2 °C, and 3 °C warming (figures 5 and 6). Overall, there are three regimes driving the increase in the regional CDHEs (i.e. decrease in the SDHI). First, in the west coast of South America, Southern Europe and the Mediterranean, the decreases in the SDHI are driven by compound
Figure 5. Changes in the warm season (a)–(c) temperature (K) and (d)–(f) precipitation (mm) from the baseline period to 1.5 °C, 2 °C, and 3 °C warming. The legend in (a) applies to (b), (c), the legend in (d) applies to (e), (f). The hatching indicates the changes that are significant according to the Wilcoxon Sign Test (95% confidence).

Figure 6. Regional changes in the warm season (a)–(c) temperature (K) and (d)–(f) precipitation (mm) from the baseline period to 1.5 °C, 2 °C, and 3 °C warming. The colors show the multi-model maximum (red), multi-model minimum (blue), and multi-model ensemble median (the dividing line between the blue and red colors).
Table 2. Regional changes in the warm season SDHI, temperature and precipitation from the baseline period to 1.5 °C warming, from the 1.5 °C to 2 °C warming, and from the 2 °C to 3 °C warming in central America and Mexico, the Amazon, Southeast Asia, and north Australia. The asterisk indicates that the change is statistically significant across all climate models used according to the Wilcoxon Sign Test (95% confidence).

| Regions                  | +1.5 °C minus baseline SDHI | +2.0 °C minus +1.5 °C SDHI | +3.0 °C minus +2.0 °C SDHI |
|--------------------------|-----------------------------|-----------------------------|-----------------------------|
|                          | P (mm)                      | T (K)                       | P (mm)                      | T (K) |
| Central America and Mexico | −0.80*                      | 4.42                        | 1.18                        |       |
| The Amazon               | −0.82*                      | 1.84                        | 1.65*                       |       |
| Southeast Asia           | −0.85*                      | 12.75*                      | 0.93*                       |       |
| North Australia          | −0.64*                      | 0.40                        | 1.27*                       |       |

changes in both temperature and precipitation (i.e. simultaneous increase in temperature and drying; Regime 1). Second, globally and in most regions (e.g. Alaska, Northwestern Canada, Eastern Canada, Greenland, Iceland, western North America, central North America, Central Europe, the Sahara, eastern North America, northeastern Brazil, southeastern South America, Northern Europe, East Arica, North Asia, West Asia, Central Asia, the Tibetan Plateau, East Asia, and South Asia), the SDHI decreases with warming, which dominates over the reduced drought risk (i.e. precipitation increases significantly under 1.5 °C, 2 °C, and 3 °C warming; Regime 2). The distributions of warm-season precipitation widen in these regions, so despite the increase in the mean trend of the precipitation there is an increasing risk of more extreme CDHEs. Third, in central America, Mexico, the Amazon, Southeast Asia, and north Australia, the decreases in the SDHI are driven by warming with either decreased or increased precipitation (Regime 3). Regime 3 reflects a transition between Regime 1 and Regime 2. For example, the decreases in the SDHI from the baseline period to 1.5 °C warming, from the 1.5 °C to 2 °C warming, and from the 2 °C to 3 °C warming in central America, Mexico, and the Amazon (Regime 2 to Regime 1; precipitation increases from the baseline period to 1.5 °C warming, but decrease from the 1.5 °C to 2 °C to 3 °C warming) shows an obviously regime transition (table 2).

4.3. Uncertainty

There are several sources of uncertainty in this study. The most important is the uncertainty from precipitation and temperature simulations in the different climate models. Generally, the uncertainty of the precipitation (including the mean and extremes) is larger than that of the temperature (figure 5) in both the CMIP6 and CMIP5 models (Kim et al 2020, Li et al 2021). These uncertainties are translated to the SDHI calculations spatially and temporally on both the global and regional scales. For example, the large uncertainty in the warm season precipitation in the Sahara leads to uncertainty in the SDHI under 1.5 °C, 2 °C, and 3 °C warming (figures 2 and 5).

The use of multiple GCMs allows for the better synthesis of the future projections than a single model. Moreover, the application of a bias correction would help adjust the absolute value of the target GCM output to that of the observation, so that their distributions would be consistent. However, recent climate change studies (e.g. Sun et al 2011, Maraun 2016) have demonstrated that the calculated changes between the historical and future period with and without bias-correction are quite similar, which is because the similar statistical adjustments made to the future and historical period canceled one another. Thus, a bias correction was not used in this large-scale study, which focused on climate change projections under different warming levels (e.g. 1.5 °C, 2 °C, and greater) relative to the baseline period.

There are many approaches to assessing CDHEs. The traditional threshold methods mostly focus on the frequency of the variability, which enables the detection of variations in the CDHEs but fails to determine their severity levels (Hao et al 2013, Wu et al 2020). Compared to the traditional approaches, the SDHI approach applied in this study can better capture the severity and spatial extent of the CDHEs. The use of a single CDHE index may have introduced uncertainty in this study. However, it is an easy-to-use and widely applied tool for quantifying the spatial extent and severity of CDHEs considering the multivariate factors associated with extremes (Hao et al 2018, Wu et al 2020). In the calculation of the SDHI, F(X) was standardized using standard normal distribution fitted with data from 1980 to 2100 (including the climate model outputs of monthly precipitation and temperature from both the historical and RCP5-8.5 scenarios) for each grid, which made the estimated SDHI and its sensitivity geographically comparable at the different warming levels. Further discussions of how the definition of the SDHI influences the results and comparisons of different approaches are important but are beyond the scope of this study. Finally, the use of a single SSP5-8.5 scenario and SSP5 population data would also introduce uncertainty into this study. Despite these sources of uncertainty, overall, the projected changes in the CDHEs and their population exposures are robust according to the Wilcoxon Sign Test across most regions.
5. Conclusion

Based on the outputs of newly released CMIP6 climate models and global population datasets, the future CDHE changes and their population impacts were projected under 1.5 °C, 2 °C and 3 °C warming on both the global and regional scales. It was confirmed that the severity of CDHEs will increase on both the global and regional scales, especially in Southern Europe, the Mediterranean, the Sahara, West Africa, Central America, Mexico, the Amazon, and the west coast of South America. However, the actual drivers (changes in precipitation, temperature and potentially their feedbacks) of the changes in the warm season SDHI are regionally different. By limiting global warming to 1.5 °C instead of 2 °C and 3 °C above preindustrial levels, the number of people affected by severe CDHEs would decrease by 108 and 266 million (pop2000) globally. It would spare 149 and 367 million people from severe CDHEs if the pop2080 is applied. Under 1.5 °C, 2 °C and 3 °C warming, more people (pop2000) would be exposed to severe CDHEs in Central Europe, Southern Europe, the Mediterranean, West Asia, eastern North America, Central Asia, East Asia, and Southeast Asia. The severe CDHE population exposures would further increase in most regions, except for East Asia, North Asia, the Tibetan Plateau, northeastern Brazil, and the west coast of South America when the pop2080 is used. These findings provide scientific evidence on the benefit of limiting anthropogenic warming to 1.5 °C and help in mitigating or avoiding CDHE-related socio-economic risks.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://esgf-node.llnl.gov/search/cmip6/.

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