Anthropogenically forced increases in compound dry and hot events at the global and continental scales

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Abstract
Remarkable increases in compound dry and hot events (CDHEs) have been observed in different regions in recent decades. However, the anthropogenic influence on the long-term changes in CDHEs at the global scale has been largely unquantified. In this study, we provide evidence that anthropogenic forcings have contributed to the increased CDHEs over global land areas. We compare the spatial and temporal changes in CDHEs based on climate model simulations from Coupled Model Intercomparison Project Phase 6 and observations from different datasets. The results show observed occurrences of CDHEs have increased over most regions across global land areas during 1956–2010 relative to 1901–1955. In addition, we find a temporal increase in observed occurrences of CDHEs averaged over global land areas and different continents (except Antarctica) for the period 1901–2010 (with a larger increase during 1951–2010). The spatial and temporal changes in historical all-forcing simulations (with both anthropogenic and natural components) are overall consistent with observations, while those in historical natural-forcing simulations diverge substantially from observations, heightening the key role of anthropogenic forcings in increased CDHEs. Furthermore, we use the probability ratio (PR) to quantify the contribution of anthropogenic forcings to the likelihood of CDHEs since the mid-20th century (1951–2010). We find anthropogenic influences have increased the risk of CDHEs in large regions across the globe except for parts of Eurasia and North America. Overall, our study highlights the important role of anthropogenic influences in increased CDHEs from a global perspective. The mitigation of climate change is thus paramount to reduce the risk of CDHEs.

1. Introduction
Global temperature increases due to anthropogenic greenhouse gas emissions are associated with changes in weather and climate extremes at different temporal and spatial scales (He et al 2020, Perkins-Kirkpatrick and Lewis 2020, La Sorte et al 2021, Sun et al 2021a). Droughts and high-temperature (or hot) extremes are among the most catastrophic natural hazards and can cause severe losses and damage to the economy, agriculture, and public health. Mounting evidence has shown an increase in the frequency, intensity, and spatial extent of the two extremes at the global scales (Coumou and Robinson 2013, Dai 2013, Cook et al 2018), highlighting potentially augmented impacts from these extremes. As a result, it is critically important to understand the causes of their changes under human-induced global warming.

Attribution of droughts and hot extremes, including long-term changes and specific events, to anthropogenic influence has been extensively explored at regional and global scales based on model simulations of historical climate series with and without anthropogenic forcings (Bindoff et al 2013, Jones et al 2013, Sun et al 2014, 2021b, Fischer and Knutti 2015, Zhai et al 2018, Wang et al 2020). The anthropogenic influence on hot extremes has been widely reported with high confidence (Bindoff et al 2013, Jones et al 2013, King et al 2015, Sun et al 2017, Li et al 2020a). Although there are large uncer-
tainties in the attribution assessment of precipitation (or drought) changes due to observational/modeling uncertainties and large internal variability (Bindoff et al 2013, Sarojini et al 2016, Dittus et al 2018), the emergence of anthropogenic signals in precipitation (or drought) trend has been detected at regional/national scales (Gudmundsson and Seneviratne 2016, Chen and Sun 2017, Li et al 2018a, 2021, Ye and Qian 2021) and global scales (Ukkola et al 2020, Dong et al 2020, Chiang et al 2021b). For example, Chiang et al (2021b) showed anthropogenic influences on drought frequency, duration, and intensity at the global scale. These studies mostly focused on individual droughts or hot extremes and provided useful information for climate policy in disaster prevention and mitigation.

Although there have been extensive attribution studies on isolated droughts or hot extremes, those on the concurrences of droughts and hot extremes have been limited. These events are commonly termed compound dry and hot events or extremes (CDHEs) and have strong ramifications in different sectors, such as ecology, agriculture, and socioeconomics (Hao et al 2013, Zscheischler et al 2018, Ribeiro et al 2020, Weber et al 2020, Lesk and Anderson 2021). Along with the diagnosis of characteristics and physical mechanisms of recent CDHEs (Zscheischler et al 2018, Li et al 2018b, Mukherjee et al 2020, Tavakol et al 2020, Geirinhas et al 2021, Seo et al 2021), attribution of the occurrence of these events (or event attribution) based on Coupled Model Intercomparison Project Phases 5 and 6 (CMIP5 and CMIP6) has emerged in recent years (Yuan et al 2018, Chiang et al 2021a, Wang et al 2021, Wu et al 2021a, Zscheischler and Lehner 2021). For instance, Wang et al (2021) suggested that anthropogenic climate change increased the likelihood of extremely hot and dry weather in spring–early summer of 2019 in southwestern China. Yuan et al (2018) found that in addition to the strong El Niño, anthropogenic climate change likely increased the likelihood of the concurrence of soil moisture droughts and heatwaves during the summer of 2015/2016 in South Africa. The attribution of the long-term changes of CDHEs at different regional scales has also emerged (Diffenbaugh et al 2015, Sarhadi et al 2018, Cheng et al 2019, Li et al 2020b, Mishra et al 2021). Based on the joint probability-based indicator to represent CDHEs, Li et al (2020b) used the optimal fingerprinting method to attribute the CDHEs based on CMIP5 simulations and suggested that anthropogenic activity was the crucial factor in the increases of CDHEs in northeastern China. However, the attribution of long-term changes in the occurrence of CDHEs at the global (and continental) scale based on the latest CMIP6 model simulations is rather limited.

The objective of this study is to explore anthropogenic influences on the occurrence of CDHEs at global scales based on CMIP6 models over the period 1901–2010. Based on the comparison of observations with simulations under different scenarios, the spatial and temporal changes in CDHEs and associated anthropogenic influences were evaluated. The contribution of anthropogenic factors to CDHE changes across different continents and sub-periods was also assessed. Finally, anthropogenic influences on the occurrence probability of CDHEs for the period 1951–2010 over global land areas were quantified based on the probability ratio (PR). This study is useful for understanding the influence of anthropogenic climate change on compound events or extremes.

### 2. Data and methods

#### 2.1. Data

In this study, three monthly precipitation and temperature datasets at the global scale are used as observations. The first was obtained from the Climatic Research Unit (CRU TS v4.05) (Harris et al 2020), which is interpolated from individual weather stations over global land areas. The second was obtained from the University of Delaware (UDEL v5.01) (Willmott and Matsuura 2001), which contains a large number of stations from the Global Historical Climate Network (GHCN2) and other sources. Compared to the gauge-based CRU and UDEL datasets, the third dataset from Princeton Global Forcing (PGF v2) (Sheffield et al 2006) merges the reanalysis products from the National Centers for Environmental Prediction (NCEP) and National Center for Atmospheric Research (NCAR) with several satellite-based and gauge-based datasets. These three datasets all have a resolution of $0.5^\circ \times 0.5^\circ$ and cover the full study period 1901–2010. We select these datasets to assess the sensitivity of attribution results to observations. We mainly analyze the results based on CRU and those based on the other two datasets are shown in supplementary materials.

Fourteen models (using one ensemble member per model) from CMIP6 are used to obtain the historical simulations (table S1 available online at stacks.iop.org/ERL/17/024018/mmedia) spanning from 1901 to 2010 under two scenarios, including those based on all forcings (ALL: both natural and anthropogenic forcings) and natural forcings (NAT), respectively. The comparison of ALL and NAT simulations reflects the impact of anthropogenic influence. In this study, sub-regions of global land areas are defined as the six continents (as shown in figure S1), including North America, South America, Europe, Africa, Asia, and Australia (Antarctica is not considered due to the lack of complete observations). Following Sheffield et al (2012), we also mask
out Greenland and desert regions (precipitation less than 0.5 mm d\(^{-1}\)) without calculation of dry events (with approximately zero mean precipitation), since a percentile-based drought index is meaningless in these regions (Dunn et al. 2020). All observed and simulated data are projected onto a 1° × 1° spatial resolution and masked by global land areas to ensure consistent comparisons between observations and model simulations. The multi-model average from model simulations of historical experiments is computed for the subsequent analysis, which reduces internal variability and results in predominantly forced signals in the averaged model response (Jones et al. 2013).

2.2. Method

2.2.1. Defining compound dry and hot events

In this study, individual dry and hot events are defined based on the relative threshold for each month (Zscheischler and Seneviratne 2017, Hao et al. 2019), namely monthly precipitation lower than the 30th percentile and monthly temperature higher than the 70th percentile, respectively. Considering model biases, the thresholds of simulations are computed for each model (from ALL simulations) and the thresholds of observations are computed for each dataset during the base period 1961–1990. This base period was recommended by the World Meteorological Organization and has been widely used in the definition of extremes under climate change (Jones et al. 2013, Sun et al. 2017, Feng et al. 2020). We define CDHEs as the concurrence of dry and hot events (i.e. \(P \leq 30\text{th percentile and } T > 70\text{th percentile}\)) for each month (Hao et al. 2013, Zscheischler and Seneviratne 2017). Note that the occurrence of CDHEs based on these thresholds only indicates a moderate level of dry and hot conditions compared with the climatological average in the same month. We choose these thresholds to extract large samples of events and alleviate the uncertainties caused by limited samples. The relative changes in CDHEs for each grid are defined as the difference in the number of occurrences between the two equal periods (1956–2010 versus 1901–1955) divided by that in the first period (1901–1955). To further explore temporal changes in CDHEs, the average number of occurrences of CDHEs for all grids over the study regions per year is calculated for trend analysis. CDHEs defined by other thresholds (e.g. \(P \leq 50\text{th percentile and } T > 50\text{th percentile}\)) are also computed and similar patterns are obtained (not shown).

2.2.2. Model evaluation

Before attribution analysis, we use two evaluation metrics to describe the performance of each model (under ALL forcing). Following Ridder et al. (2021), we evaluate the performance of models in simulating CDHEs in each continent based on the skill score. The skill score presents the consistency between the distribution of simulated and observed numbers of occurrences of CDHEs. Specifically, the skill score can be expressed as follows:

\[
S_{\text{skill}} = \frac{1}{n} \sum_{i=1}^{n} \min(Z_{i}^{\text{obs}}, Z_{i}^{\text{mod}})
\]

where \(Z_{i}^{\text{obs}}\) and \(Z_{i}^{\text{mod}}\) (i = 1, 2, ..., n) are the observed and simulated frequency of occurrences at each bin for all grids for a certain region, respectively (n is the number of bins) (Perkins et al. 2007). \(S_{\text{skill}}\) is the sum of minima between \(Z_{i}^{\text{obs}}\) and \(Z_{i}^{\text{mod}}\) for all bins. The skill score ranges from 0 to 1 (a value of 1 represents a perfect reproduction of observations and a value of 0 represents unreliable simulations).

In addition, the probability of detection (POD) is employed to examine the capability of different models to capture the sign of changes in observations. POD is defined as the ratio of the number of grids where the simulations from a single model and observations give the same sign of changes (increase, decrease, or neutral) to the number of total grids in the study regions (Hao et al. 2013, Wu et al. 2021b).

2.2.3. Attribution analysis

The anthropogenic influence on the long-term changes in CDHEs is assessed by comparing the spatial and temporal changes from the simulations, including and excluding anthropogenic forcings, with those from observations. Specifically, when the changing pattern of observations is consistent with that of ALL simulations while inconsistent with that of NAT simulations, the observed changes can be attributed to anthropogenic forcings. The contribution of anthropogenic forcings to the probability of CDHEs can be quantified based on PR (Stott et al. 2016, Otto 2017, Zhou et al. 2021). This method has recently been extended to the attribution of extreme events exceeding a certain threshold from climatology (e.g. hot extremes, drought, and heavy precipitation) (Fischer and Knutti 2015). The equation of PR can be expressed as:

\[
PR = \frac{P_{\text{ALL}}}{P_{\text{NAT}}}
\]

where \(P_{\text{ALL}}\) and \(P_{\text{NAT}}\) represent the probability of occurrence of such events (i.e. CDHEs) under ALL forcing and NAT forcing, respectively. Here the probability of CDHEs for each grid is empirically defined as the number of occurrences divided by the total number of periods (Fischer and Knutti 2015, Ridder et al. 2020, Zhang et al. 2020). The anthropogenic forcings increase the likelihood of CDHEs when PR > 1 and vice versa.

3. Results

3.1. Spatial changes from observations and simulations

We first evaluate the performance of models in simulating the climatology and changes of CDHEs.
The ability of models to simulate the occurrence of CDHEs is shown by the skill score (figure S2). The results show that these climate models perform relatively well in large regions (with skill scores higher than 0.5), including North America, Europe, Asia, and Africa, and perform relatively poorly in South America and Australia. The capability of models to capture the changes of CDHEs is presented by the probability of detection (POD) (figure S3). Among all the models used in this study, simulations show the same sign of changes with the observations (from different datasets) in 52.2% to 81.5% of study areas. Overall, the results imply that these model simulations are useful for the attribution analysis of CDHEs in large regions.

To assess the contribution of anthropogenic influences to spatial changes in CDHEs at the global scale, we compute spatial changes in the occurrence of CDHEs for observations (from CRU) and the multi-model average of simulations under different scenarios, as shown in figure 1. A two-sample t-test is used to examine the significance of differences between the CDHEs occurrences in two periods (Wilks 2011). The stippling is plotted (at a 2° × 2° resolution) when observations in figure 1(a) or at least 50% of models in figures 1(b) and (c) show statistically significant changes (at the 0.05 significance level).

From a global perspective, most areas (82.29%) show increased CDHEs in observations from CRU (figure 1(a)). The multi-model average of simulations under ALL forcing shows an overall increase in CDHEs across most land areas (99.35%) with certain overestimation of increased areas (figure 1(b)). Most models show significant changes at low latitudes, which is overall consistent with observations (figure S4). Note that in eastern North America and northern Eurasia, observational results show a decrease in CDHEs. However, the ALL simulations can barely capture this pattern, which may limit the confidence in attribution assessments in these regions. Contrastingly, the multi-model average under natural-only forcings shows insignificant changes with decreased CDHEs in a large portion of global land areas (figure 1(c)), which cannot explain the observed increases in CDHEs (results from single models indicate similar patterns as shown in figure S5). The results using other observational datasets show similar patterns (figures S6 and S7), though certain differences exist in some regions like Asia. Overall, the increased CDHEs in most regions at the global scale are not necessarily caused by natural climate variations, and are more likely to be affected by anthropogenic climate change.

3.2. Temporal changes from observations and simulations

3.2.1. Changes at the global scale

The comparison of temporal changes in annual occurrences of CDHEs for the period 1901–2010 averaged over global land areas based on CMIP6 model simulations with those based on observations (CRU) is shown in figure 2. The 5%–95% ranges of the time series from multi-model simulations are computed to represent the uncertainty. The trend analysis of the average annual occurrences of CDHEs based on the nonparametric Mann–Kendall (M–K) test is shown in figure 2 (with Sen’s slope and p-value). The results of occurrence changes in CDHEs from ALL simulations are closer to observations (than the NAT simulations) and capture their general temporal features, which is consistent with previous studies (Wu et al 2021b). For example, the temporal changes in CDHEs, including slight increases from the 1900s–1940s, fluctuations during the 1950s–1970s, and continuing increases from the 1980s, are shown from both observations and simulations. The overall similar pattern of global temperature increase during these periods (Jones et al 2013) and the small increase in global precipitation over the 20th century (Hartmann et al 2013) from observations imply the dominant role of temperature increase in driving changes in CDHEs. The observed occurrences of CDHEs show significant increases, with a slope of 0.119/decade. Meanwhile, the ALL simulations reproduce the increasing trend (with a slope of 0.063/decade) of the occurrence of CDHEs, though some underestimations of trends exist. The temporal increase from the observations lies generally within the spread of historical ALL simulations (especially for the recent periods from the 1980s). These results indicate that the historical ALL simulations from models capture the temporal changes in observations relatively well.

On the other hand, the NAT simulations of the occurrence of CDHEs indicate a slightly decreasing trend (with a slope of −0.006/decade). Large discrepancies are shown between observations and multi-model averages of NAT simulations. The spread of model simulations under NAT forcing diverges substantially from observations in recent decades (especially after the 1980s). This pattern suggests that the increased occurrence of CDHEs is not likely to occur without anthropogenic climate change. These results, combined with results from ALL simulations, heighten the important role of anthropogenic forcings in driving the temporal changes of CDHEs. The temporal changes in observed CDHEs from different data sources at the global scale show roughly similar patterns (though certain differences exist in the first half of the 20th century), as shown in figures S8 and S9.

The study periods are divided into two common periods (1901–1950 and 1951–2010) to evaluate changes at different periods (Jones et al 2013). The linear trends of CDHE occurrences from simulations and observations (from CRU, UDEL, and PGF) for different periods are shown in table 1. Significant increases are found in each sub-period for all three observational datasets. ALL simulations capture the
Figure 1. Spatial changes in the occurrences of CDHEs over global land areas between 1956–2010 and 1901–1955 from the observations based on CRU (a) and CMIP6 model simulations under ALL forcing (b) and NAT forcing (c). The percentage at the bottom left of each panel represents the ratio of the number of grid points with increased CDHEs to the total number of grid points. Stippling in (a) indicates the areas where observations show significant changes between two periods at the 0.05 significance level based on the two-sample t-test. Stippling in (b) and (c) indicates areas where at least 50% of models show significant changes.
Figure 2. Temporal changes in average annual occurrences of CDHEs over global land areas based on observations (CRU) and CMIP6 model simulations (ALL and NAT) during the period 1901–2010. The solid lines are the time series based on observations and multi-model average simulations. The dashed lines are the linear trends with slopes estimated by the M–K trend test. The shading indicates the 5%–95% ranges for multi-model simulations.

Table 1. Linear trends (per decade) of average annual occurrences of CDHEs over global land areas based on observations (CRU, UDEL, and PGF) and CMIP6 model simulations (ALL and NAT) during different periods.

|                 | 1901–2010 | 1901–1950 | 1951–2010 |
|-----------------|-----------|-----------|-----------|
| CRU             | 0.119     | 0.177     | 0.180     |
| UDEL            | 0.057     | 0.093     | 0.193     |
| PGF             | 0.108     | 0.189     | 0.174     |
| ALL             | 0.063     | 0.067     | 0.170     |
| NAT             | −0.006    | 0.039     | 0.008     |

* The trend is significant at the 0.05 significance level.

increasing trend in each period of observations. Specifically, the trend in the latter period (1951–2010) given by ALL simulations (with a slope of 0.170/decade) is relatively similar to that given by observations (with slopes of 0.180/decade, 0.193/decade, and 0.174/decade). On the other hand, the variations estimated by NAT simulations are weak and not significant. It can be concluded that anthropogenic forcings contribute to the increases in CDHEs, especially in recent decades. However, we note that there are certain discrepancies in observations from different datasets, especially in the first half of the 20th century when meteorological stations are limited. The observational uncertainties may limit the confidence of the attribution.

3.2.2. Changes at the continental scale

Figure 3 shows the temporal changes in CDHEs at the continental scale using observations from CRU (results from other datasets are shown in figures S10 and S11) with the linear trends shown in Table 2 for the period 1901–2010 (table S2 for the period 1951–2010). The annual occurrences of CDHEs show overall increases in each continent, though certain differences do exist from various datasets. Relatively large increases in the observed occurrence of CDHEs are found in Africa and South America. ALL simulations can generally capture the significantly increasing trend of observed CDHEs at the regional scale (with slopes of 0.027–0.138/decade). However, NAT simulations show weak variation in each continent (with slopes of −0.012–0.001/decade) and diverge remarkably from the observations in recent decades. The comparison of these trends suggests the critical contribution of anthropogenic forcings to the increase in CDHEs across different continents. Note that the attributions at the continental scale and subcontinental scale are less reliable than those at the global scale (Zhai et al 2018). For instance, there are relatively large uncertainty ranges in the results from model simulations in some continents, such as Australia (figure S2) (Ridder et al 2021), which may influence the confidence of the attribution.

3.3. Probability ratio under different scenarios

The attribution of spatial–temporal changes in CDHEs in previous sections shows anthropogenic forcings have had larger impacts since the mid-20th century. To further quantify the influence of anthropogenic forcings on the occurrence probability of CDHEs for the period 1951–2010, we compute the multi-model average of PR for CDHE occurrences, as shown in figure 4. The results show that anthropogenic forcings promote the occurrence of CDHEs in large regions (with PR > 1). For instance, in the tropics, anthropogenic climate change caused a more
than three-fold increase in the probability of CDHEs. The large influence of anthropogenic forcings on CDHEs over the tropics likely results from hotter and drier backgrounds caused by anthropogenic climate change (Chiang et al 2021a, 2021b). At mid-to-high latitudes, anthropogenic forcings increase the probability of CDHEs slightly. The anthropogenic forcings even reduce the probability of CDHEs (PR < 1) in parts of the mid-latitudes of the northern hemisphere (or parts of Eurasia and North America), which may be related to the significant contribution of anthropogenic forcings to increases in precipitation (Zhang et al 2007). In addition, the uncertainty range of PR is evaluated based on the 25th, 50th, and 75th percentiles of PR estimated from multi-model simulations, as shown in figure S12. It can be seen that most models show a positive contribution of anthropogenic forcings to the likelihood of CDHE in the tropics. However, the PR shows relatively large differences among individual models in mid-to-high latitudes in the northern hemisphere, which causes uncertainties associated with PR results. In general, anthropogenic climate changes have increased the risk of CDHEs during 1951–2010 in most regions of the globe.

4. Discussion

The confidence of the CDHE attribution in this study is closely related to the uncertainty in attributing individual droughts and hot extremes. According to previous studies, the attribution of extremes related to temperature (e.g. heat waves) has relatively high confidence even at the regional scale (Bindoff et al 2013, Yin et al 2017, Zhai et al 2018). Compared to temperature, precipitation variations are more affected by the internal climate variability, especially at the regional scale (Dai et al 2018). Because of the high level of internal variability, high uncertainty and low signal-to-noise ratio have been shown for the precipitation attribution. Accordingly, the confidence in attributing drought changes over global land areas to anthropogenic influences is still low (Bindoff et al 2013, Zhai et al 2018). The finding of the increasing trend of occurrence of CDHEs at the global scale due to anthropogenic influence is likely dominated by

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**Table 2.** Linear trends (per decade) of average annual occurrences of CDHEs over six continents based on observations (CRU, UDEL, and PGF) and CMIP6 model simulations (ALL and NAT) for 1901–2010.

|                | CRU   | UDEL  | PGF   | ALL   | NAT   |
|----------------|-------|-------|-------|-------|-------|
| North America  | 0.091 | 0.029 | 0.080 | 0.041 | -0.001|
| South America  | 0.146 | 0.101 | 0.128 | 0.038 | -0.003|
| Europe         | 0.055 | 0.039 | 0.052 | 0.027 | -0.012|
| Africa         | 0.180 | 0.131 | 0.190 | 0.121 | -0.008|
| Asia           | 0.116 | 0.041 | 0.107 | 0.043 | -0.006|
| Australia      | 0.075 | 0.067 | 0.064 | 0.073 | -0.009|

* The trend is significant at the 0.05 significance level.
the strong signal of temperature increases. However, the relative importance of droughts and hot extremes in attributing CDHEs is still unquantified. In addition, we focused on the influence of anthropogenic forcings on the occurrence probability of CDHEs for the recent period 1951–2010. For the warming during the early 20th century (i.e. 1910–1940), the influence of internal variability and/or anthropogenic forcing (or other external forcings such as solar activity) is still open to debate (Egorova et al 2018, Hegerl et al 2018), adding complexity in attributing the occurrence probability of CDHEs during this period.

The attribution assessments in this study rely on climate model simulations, which are subject to model biases. The skill of CMIP6 models at simulating extreme events of temperature and precipitation remains to be improved (Bador et al 2020, Di Luca et al 2020). These model biases could be related to the lack of accurate representation of fine-scale processes (e.g. land–atmosphere interactions) or sea surface temperature anomalies in different oceans from the CMIP5/CMIP6 models (Wang et al 2014), which are closely related to extremes including CDHEs (Hao et al 2019, Mukherjee et al 2020). The evaluation of climate models in simulating compound droughts and hot extremes has been conducted at global scales (Hao et al 2013, Ridder et al 2021, Wu et al 2021b). Ridder et al (2021) provided a comparison between CMIP6 models and observations in estimating compound droughts and heatwaves, which showed overall similar patterns in North America, Europe, and Eurasia but large biases in Australia. The model evaluation in this study further shows that model performances may differ in simulating different aspects of compound events (e.g. good performance in simulating climatology but relatively poor performance in simulating changes in North America, as shown in figure S2 and figure 1, respectively). The evaluation of climate models in simulating extremes, especially compound extremes, remains a challenge and improved evaluation approaches need to be explored. The uncertainties result not only from models but also from observations (Vogel et al 2019). We acknowledge that there exists a certain disparity in observed changes in CDHEs computed from different observational datasets, which may influence the detection and attribution of CDHEs. The lack of observations before the 1950s (Jones et al 2013) may also induce uncertainties in observed changes in CDHEs and attribution results. Overall, uncertainties from models (e.g. fine-scale processes) and observations (e.g. limited records before the 1950s, difficulties in setting apart decadal drought variability from long-term trends) may still limit a precise statement about attribution confidence. It can be expected that improved climate models and observations will improve the confidence in attributing compound events in future research.

5. Conclusion

This study shows that the long-term increase in the occurrence of CDHEs for the period 1901–2010 at the global and continental scales cannot be explained
by natural climate variability, heightening the anthropogenic influences in driving these changes. For the spatial changes of CDHEs, the ALL simulations can overall capture observed increases in CDHEs across most regions over global land areas (though certain overestimations of increased areas exist). In general, it is almost impossible to simulate the observed CDHE variability without anthropogenic forcings. For the temporal changes in the CDHEs during 1901–2010, the trends (or slopes) in the occurrences of CDHEs over global land areas are 0.057 ∼ 0.119/decade, 0.063/decade, and −0.006/decade for observations (from different datasets), historical ALL simulations, and historical NAT simulations, respectively. The ALL simulations can capture the overall pattern of the temporal changes from observations, while large discrepancies exist between the NAT simulations and observations. Over the period 1951–2010, ALL simulations and observations show relatively similar trends. The comparison of observations with ALL and NAT simulations demonstrates that the temporal and spatial changes are largely attributable to human influence. We also employ the PR to quantify the contribution of anthropogenic forcings to the likelihood of CDHEs for the period 1951–2010 (when anthropogenic forcings have a stronger influence on CDHEs). We find that anthropogenic influences increase the probability of occurrence of CDHEs in large regions, especially in the tropics. It should be noted that observations based on different datasets show broadly consistent patterns of increased CDHEs at the global and continental scales, implying the robustness of this study. Notwithstanding uncertainties in model simulations, our study shows the potentially significant role of human-induced climate change in explaining observed increases in CDHEs since the start of the 20th century. Thus, limiting greenhouse gases to mitigate climate change is crucial to reducing the risk of CDHEs.

Data availability statements

The data that support the findings of this study are openly available at the following URL/DOI: http://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.05/ https://psl.noaa.gov/data/gridded/data.UDel_AirT_Precip.html https://hydrology.princeton.edu/data/pgf/v2/ and https://esgf-node.llnl.gov/projects/cmip6/.

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