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RESEARCH ARTICLE

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Changes of compound hot and dry extremes on different land surface conditions in China during 1957–2018

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Abstract

The co-occurrence of hot and dry extremes (compound hot and dry extreme, CHDE) has attracted much attention due to the amplified impact on wildfire occurrence, agriculture production and human health. Most existing studies have reported the spatiotemporal variations of CHDE, changes in CHDE on different land surface conditions are barely discussed. The study investigated the spatial and temporal differences of CHDE over different regions and land covers in China during 1957–2018. On average over China, both day- and night-time CHDEs have increased with a more rapid (2.6 times faster) and significant ($p < .05$) increasing trend in night-time ones. Increasing trends are mainly distributed in north China with decreasing trends in central China. Moreover, increasing trends in night-time mildly dry (0.07 per decade) and moderately hot (0.06 per decade) CHDEs are the largest among all dry and hot CHDEs. Regionally, the frequency of CHDE is the highest over the humid and sub-humid regions for night- and day-time CHDEs, but the lowest for both over the arid region. Meanwhile, CHDE has increased over the humid and sub-humid regions in the recent decade but decreased over the arid region since 1957. For different land covers, the frequency of CHDE is the highest over forest but the lowest over grassland. Day-time CHDEs of different hot magnitudes indicate the largest increasing trends over grassland caused by the largest increasing trends of day-time heatwave. Significant ($p < 0.05$) increasing trends of day- and night-time CHDEs over forest may increase the risks of tree mortality or forest fires after 2010 and larger increasing trends in night-time CHDEs over urban may negatively impact human health.

KEYWORDS

arid and humid regions, CHDE, China, land covers

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1 | INTRODUCTION

Global warming has triggered increasing heatwave and drought, posing devastating impacts on natural systems and human society (Zscheischler and Seneviratne, 2017). Heatwaves have been extensively studied for causing high mortality (Rahmstorf and Coumou, 2011) and droughts have been widely investigated given the impact on agriculture, hydrology and snowpacks (Zhang *et al*., 2019; Dai *et al*., 2020; Guo *et al*., 2020). The co-occurrence of heatwave and drought, defined as compound hot and dry extreme (IPCC, 2012) (CHDE), can present amplified risks (Hao *et al*., 2018). For example, the 2003 European summer heatwave and severe drought have caused around 70,000 deaths (Robine *et al*., 2008) and the 2019 heatwave and drought in south Australia have triggered multiple forest fires. Therefore, the investigation of CHDE is of great significance considering the subsequent risks.

Heatwave and drought are likely to occur jointly as they are both characterized by extremely low precipitation. The 2003 European and 2010 Russian heatwaves are accompanied by severe droughts (Miralles *et al*., 2014; Russo *et al*., 2015). The 2014 California drought stands out by not only low precipitation but also extremely high temperatures (AghaKouchak *et al*., 2014). Therefore, with the increasing heatwave and drought (Dai, 2013; Huang *et al*., 2017), CHDE has correspondingly increased in the frequency, intensity and spatial extent (Hao *et al*., 2013, 2018; Sharma and Mujumdar, 2017). Copula function is applied to discuss the joint probability of CHDE with increasing probability detected (AghaKouchak *et al*., 2014; Gebrechorkos *et al*., 2019; Hao *et al*., 2020). Lu *et al*. (2018) have concluded that increasing CHDE during growing seasons could seriously affect wheat and maize production in China. Coffel *et al*. (2019) predicted that future hot and dry years would worsen Nile basin water scarcity despite the projected precipitation increase. Anderegg *et al*. (2013) also pointed out that compound drought and temperature stress could trigger widespread tree mortality. More total and urban populations would be exposed to severe drought globally and regionally in 1.5 and 2°C warmer world (Liu *et al*., 2018). The occurrence of CHDE at a global scale during the warm season is largely influenced by El Niño–Southern Oscillation (Hao *et al*., 2018). Meanwhile, the anthropogenic climate forcing has doubled the joint probability of warm and dry years relative to the 1961–1990 baseline (Sarhadi *et al*., 2018).

Existing research has reported the spatiotemporal changes, consequences and driving mechanisms of CHDE both regionally and globally. However, changes in CHDE over different land surface conditions need further efforts. Land surface conditions influence the partitioning of available energy between latent and sensible heat and can, therefore, mitigate or amplify heat extremes (Seneviratne *et al*., 2010). Soil moisture in wet regions contributes to more latent heat but less sensible heat, which limits the increase in temperature. Whereas, soils in water-limited regions reduce latent heat but increases sensible heat, which amplifies air temperature (Ukkola *et al*., 2018). Moreover, the exclusion of vegetation response to elevated CO_2 in climate projections results in a substantial global drying trend, which contradicts with a reduction in the future aridity by the Coupled Model Intercomparison Project Phase 5 (CMIP5) in many regions (Yang *et al*., 2019). Given the above facts, variations of CHDE over land surfaces with different hot and dry conditions and land cover types are worthy of comparison.

This study focuses on the spatiotemporal differences of CHDEs of different severity classes over different land surface conditions in China during 1957–2018. Two types of land surface conditions are considered, one with different hot and dry conditions from the humid, sub-humid, semi-arid to arid, and the other one with different land covers including forest, grassland, cropland and urban.

2 | DATA AND METHODS

2.1 | Data

Daily maximum (TX), minimum (TN) temperatures and total precipitation observations during 1957–2018 were collected from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/). This meteorological data set has been improved in data quality, however, some missing daily observations still exist due to station relocation or sensor replacement. Too much missing data may bias the results. Therefore, 303 stations with at least 95% daily temperature observations from 1957 to 2018 remained for further analysis. Less than 5% missing data were linearly interpolated using the average of daily observations on the neighbouring 4 days. A similar strategy was also applied to interpolate missing daily precipitation data at each station. Monthly total precipitation was calculated from daily observations. Land cover data with 1-km spatial resolution were collected from the Resource and Environment Data Cloud Platform (http://www.resdc.cn/Default.aspx) for the 1980s and 2015. Six land cover types are categorized in this data set including cropland, forest, grassland, water, desert and urban. Four major land covers with larger areas including forest, cropland, grassland and urban were selected for further analysis.

2.2 | Methods

To define CHDE, hot and dry extremes are described by heatwave and drought using temperature percentiles and standardized precipitation index (SPI), respectively. Heatwaves including day- and night-time heatwaves (DHW and NHW) are defined as the period with daily TX and TN above the 90th percentiles of daily TX and TN (TX90, TN90) throughout 1957–2018 for at least three consecutive days. This threshold has been widely used in previous studies (Feng and Zhao, 2015; Di Napoli *et al*., 2019; Li *et al*., 2019). DHW and NHW of three hot magnitudes from mild (HW_1), moderate (HW_2) to severe (HW_3) are defined using the 90th, 95th and 99th percentiles of daily TX (TX90, TX95 and TX99) and TN (TN90, TN95 and TN99) from 1957 to 2018 (Table 1). See Figure S1 for the temperature percentile of each station (taking TX90 as an example).

TABLE 1 Day- and night-time heatwaves of three hot magnitudes

Hot magnitudes	DHW	NHW
HW	TX > TX90	TN > TN90
Mild (HW_1)	TX90 < TX ≤ TX95	TN90 < TN ≤ TN95
Moderate (HW_2)	TX95 < TX ≤ TX99	TN95 < TN ≤ TN99
Severe (HW_3)	TX > TX99	TN > TN99

TABLE 2 Droughts of three dry magnitudes defined by SPI (3)

Dry magnitudes	SPI (3) value
D	SPI (3) < −0.5
Mild (D_I)	−1.0 ≤ SPI (3) < −0.5
Moderate (D_II)	−1.5 ≤ SPI (3) < −1.0
Severe (D_III)	SPI (3) < −1.5

The precipitation-based SPI is used to evaluate drought conditions and it is commonly applied from 1-month to multi-year scales. In this study, the 3-month SPI, hereafter as SPI (3), is calculated for each station from 1957 to 2018. A drought event is defined when SPI (3) reaches a value of −0.5 or less (Xu and Luo, 2019). Three drought conditions from mild (D_I), moderate (D_II) to severe (D_III) are defined using different SPI (3) thresholds (Thomas *et al*., 1993) (Table 2).

Computation of SPI involves fitting a gamma probability density function to a given frequency distribution of total precipitation for each station. The gamma distribution is defined by its probability density function (Equation 1).

$$g(x)=\frac{1}{\beta^{a}\Gamma(\alpha)}\chi^{\alpha-1}e^{-x/\beta} \tag{1}$$

where, x is precipitation, α and β are shape and scale parameters, which can be estimated using the maximum likelihood solution for each station (Equation 2).

$$\begin{aligned}\alpha&=\frac{1}{4A}\left(1+\sqrt{1+\frac{4A}{3}}\right)\\ \beta&=\frac{\bar{x}}{\alpha}\\ A&=\ln(\bar{x})-\frac{\sum\ln(x)}{n}\end{aligned} \tag{2}$$

n is the number of precipitation observations. $\Gamma(a)$ is given by Equation (3).

$$\Gamma(\alpha)=\int_{0}^{\infty}k^{a-1}e^{-k}dk \tag{3}$$

Then the cumulative distribution function can be calculated by Equation (4).

TABLE 3 Hot and dry compound extremes (CHDEs) of different dry and hot magnitudes

Different magnitudes	Heatwaves	Droughts	Compound extremes
Overall	DHW (NHW)	D	DCHDE (NCHDE)
Mildly hot	DHW_1 (NHW_1)	D	DCHDE_1 (NCHDE_1)
Moderately hot	DHW_2 (NHW_2)	D	DCHDE_2 (NCHDE_2)
Severely hot	DHW_3 (NHW_3)	D	DCHDE_3 (NCHDE_3)
Mildly dry	DHW (NHW)	D_I	DCHDE_I (NCHDE_I)
Moderately dry	DHW (NHW)	D_II	DCHDE_II (NCHDE_II)
Severely dry	DHW (NHW)	D_III	DCHDE_III (NCHDE_III)

I (1), II (2) and III (3) are dry (hot) magnitudes from mild, moderate to severe.

$$G(x)=\int_0^x g(x)dx=\frac{1}{\beta^{\alpha}\Gamma(\alpha)}\int_0^x x^{\alpha-1}e^{-x/\beta}dx \tag{4}$$

Since the gamma function is undefined for $x = 0$ and the precipitation distribution usually contains zeros, the cumulative probability becomes Equation (5).

$$H(x)=q+(1-q)G(x) \tag{5}$$

where, q is the probability of a zero. The cumulative probability $H(x)$ is then transformed to the standard norm random variable Z with a mean of 0 and variance of 1, which is the value of SPI (Equations 6 and 7).

FIGURE 1 Spatial distribution of 303 meteorological stations in different regions (a) and 171 stations over four major land covers (b). In the brackets are the station numbers of each category

FIGURE 2 Spatial trends (per decade) of day- (a) and night-time (b) compound extremes (DCHDE and NCHDE), MK test (UF and UB, the primary vertical axis) and temporal variations (column charts, the secondary vertical axis) of DCHDE (c) and NCHDE (d) of 303 stations from 1957 to 2018. Crosses denote trends significant at 0.05 significance level. The inserted percentages denote the station ratios in each level of trend. Numbers in the brackets present the average trends (a, b) and frequency (c, d) of DCHDE and NCHDE of 303 stations

$$Z = SPI = -\left(t - \frac{c_0 + c_1 + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad \text{for } 0 < H(x) \leq 0.5 \tag{6}$$

$$Z = SPI = +\left(t - \frac{c_0 + c_1 + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad \text{for } 0.5 < H(x) \leq 1 \tag{7}$$

where,

$$t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \quad \text{for } 0 < H(x) \leq 0.5 \tag{8}$$

$$t = \sqrt{\ln\left(\frac{1}{(1.0 - H(x))^2}\right)} \quad \text{for } 0.5 < H(x) \leq 1 \tag{9}$$

$$c_0 = 2.515517$$
$$c_1 = 0.802853$$
$$c_2 = 0.010328$$
$$d_1 = 1.432788$$
$$d_2 = 0.189269$$
$$d_3 = 0.001308$$

Based on the definitions of heatwave and drought, the occurrence of day- and night-time heatwaves in a month with SPI (3) less than −0.5 is defined as day- and night-time CHDEs (DCHDE and NCHDE). To highlight the impacts of heatwave and drought on CHDE, CHDEs of different hot or dry magnitudes, hereafter as hot or dry CHDEs, are further classified (Table 3). In hot CHDEs, droughts are defined as the month with SPI (3) less than −0.5 and heatwaves vary among different hot severity (1 ~ mild, 2 ~ moderate and 3 ~ severe). Similarly, in dry CHDEs, heatwaves are defined as the period with TX (TN) above TX90 (TN90) for three consecutive days and droughts vary among different dry severity (I ~ mild, II ~ moderate and III ~ severe).

Trends in CHDE at each station are obtained by the least square regression method to show the spatial variability. Trend analysis is conducted given the fact that long-term trends in climate extremes could be more reliable. The Mann–Kendall test (MK test) is applied with the time series of annual average frequency (f) of CHDE at 303 stations. MK test is a rank-based non-parametric method that is less sensitive to outliers compared to other parametric statistics, which has been used in previous studies (Liu and Sun, 2016; Liu *et al.*, 2018, 2019). In the MK test, UF (UB) is the (counter) rank order of the time

FIGURE 3 MK test (UF and UB, the primary vertical axis) and temporal variations (column charts, the secondary vertical axis) of day- (a1-a4) and night-time (b1-b4) compound extremes (DCHDE and NCHDE) in four different regions from 1957 to 2018. Numbers in the brackets present the average frequency of DCHDE and NCHDE of all stations in different regions

series and UF presents the temporal trend. UF values above or below zero indicate increasing or decreasing trends of the time series. Larger or smaller UF values than the critical values (±1.96 for 95% significance level) suggest significant ($p < 0.05$) increasing or decreasing trends of the time series. Also, the intersection point of UF and UB suggests an abrupt change of the time series. Significance of both spatial and temporal variations are tested at the 95% significance level.

The humid (H), sub-humid (SH), semi-arid (SA) and arid (A) regions commonly divided by 800, 400 and 200 mm precipitation isohyets in China are used to present land surfaces with different hot and dry conditions (Figure 1a). Moreover, to determine the most influential land cover type on the meteorological observations at each station, a 3-km buffer is established around each station. The land cover type that takes up the largest area above 50% of the buffer area and remains the same in the 1980s and 2015 is considered as the most influential land cover type (Feng and Zhao, 2015). Eventually, 171 stations with the same land cover in the 1980s and 2015 as forest (F), cropland (C), grassland (G) and urban (U) are selected considering the large areas (Figure 1b).

3 | RESULTS AND DISCUSSIONS

3.1 | Spatiotemporal variations of CHDE

Spatially, increasing trends are detected in the frequency of both DCHDE (0.05 per decade) and NCHDE (0.13 per decade) with an average of 2.6 times larger increasing trend in NCHDE (Figure 2a,b) across China. Xu and Luo (2019) also concluded a 2.7 times faster increase of night-time compound extremes than day-time ones in the arid and semi-arid regions of China. Moreover, significant ($p < 0.05$) increasing trends in DCHDE and NCHDE are mainly detected in north China, southwest China and south China. Decreasing trends of DCHDE are mainly distributed in northwest China and central China (Figure 2a) and those of NCHDE are largely found in central China (Figure 2b). More stations in north

FIGURE 4 Trends (per decade) in the frequency of dry CHDE (d1-d3) and hot CHDE (h1-h3) of different dry and hot magnitudes in four regions. I (1), II (2) and III (3) present mildly, moderately and severely dry (hot) conditions. H, SH, SA and A are regions from the humid, sub-humid, semi-arid to arid conditions. Numbers in the brackets present the average trends in the frequency of DCHDE and NCHDE of all stations in different regions. Error bars denote *SE*

China suggest increasing trends of CHDE, particularly that of NCHDE. This pattern is also confirmed by climate model simulations (Lu *et al.*, 2018).

Temporally, the 62-year average frequency of DCHDE (f = 1.76) is higher than that of NCHDE (f = 1.39) (Figure 2c,d). MK test suggests that DCHDE has decreased from 1957 to 2006 and increased from 2006 to 2018. However, both decreasing and increasing trends are not significant (Figure 2c). In contrast, NCHDE has increased since 1957 with an abrupt increase in 1994. An abrupt point of change in compound hot and drought extremes was also detected in 1996 in northwest China by Li *et al.* (2019). More importantly, a significant increasing trend ($p < 0.05$) in the frequency of NCHDE has been detected over China since 2002 (Figure 2d).

3.2 | Differences of CHDE in different regions

In four regions from humid to arid conditions, the 62-year average frequency of DCHDE is higher in the sub-humid (f = 1.83) and semi-arid (f = 1.81) regions than the humid (f = 1.76) and arid (f = 1.69) regions (SH > SA > H > A). However, that of NCHDE is the highest in the humid region (f = 1.44) but the lowest in the arid region (f = 1.26) with that in the sub-humid (f = 1.35) and semi-dry (f = 1.34) regions in the middle (H > SH > SA > A). The transition from non-significant decreasing to increasing trend in the frequency of DCHDE is detected over the humid, sub-humid and semi-arid regions after 2000 (Figure 3a1-a3). However, over the arid region, the frequency of DCHDE has decreased since 1957 and the decreasing trend is significant ($p < 0.05$) during 1988–2000 (Figure 3a4). In contrast, the frequency of NCHDE has increased since 1957 over the humid, sub-humid and semi-arid regions and the increasing trends are significant ($p < 0.05$) over the humid and sub-humid regions since 2000 and 2010 (Figure 3b1-b3), but that has decreased over the arid region (Figure 3b4). In general, increasing trends of CHDE are detected over the humid and sub-humid regions with the higher frequency of CHDE in the recent decades after 2000, whereas decreasing trends are found

FIGURE 5 MK test (UF and UB, the primary vertical axis) and temporal variations (column charts, the secondary vertical axis) of day- (a1-a4) and night-time (b1-b4) compound extremes (DCHDE and NCHDE) over four different land covers from 1957 to 2018. Numbers in the brackets present the average frequency of DCHDE and NCHDE of all stations over different land cover types

over the arid region with a lower frequency of CHDE since 1957.

The frequency of dry CHDEs of different dry magnitudes has generally decreased over the arid region (except for NCHDE_I) but increased over the humid region (except for DCHDE_III) (Figure 4d1-d3). Increasing trends in the frequency of DCHDE_I, NCHDE_I, DCHDE_II, NCHDE_II are the highest in the semi-arid region (Figure 4d1-d2), and those in DCHDE_III and NCHDE_III are the highest over the sub-humid region (Figure 4d3). For hot CHDEs, the frequency of moderately and severely hot CHDE has increased over four regions. DCHDE_1 and NCHDE_1 have largely increased in the sub-humid region but decreased over the arid region (Figure 4h1). Increasing trends in the frequency of DCHDE_2 and DCHDE_3 are higher in the semi-arid region whereas those of NCHDE_2 and NCHDE_3 are higher in the humid and semi-arid regions (Figure 4h2, h3). Generally, increasing trends of CHDEs of different dry and hot magnitudes are detected over the semi-arid and sub-humid regions.

3.3 | Differences of CHDE over different land covers

Over four major land cover types, the 62-year average frequency of DCHDE is higher over forest (f = 1.82) and cropland (f = 1.81) than over urban (f = 1.78) and grassland (f = 1.77) (F > C > U > G) whereas that of NCHDE is higher over forest (f = 1.42) and urban (f = 1.40) than cropland (f = 1.38) and grassland (f = 1.34) (F > U > C > G) (Figure 5). Similarly, the frequency of DCHDE has undergone a transition from non-significant decreasing to increasing trend over forest, grassland and cropland in 1987, 2006 and 2010 (Figure 5a1-a3), respectively, but generally decreased over urban since 1957 (Figure 5a4). Particularly, the increasing trend in the frequency of DCHDE is significant ($p < 0.05$) over forest after 2010. Meanwhile, the frequency of NCHDE has significantly ($p < 0.05$) increased after 2000 over forest, grassland and cropland (Figure 5b1-b3) but increased over urban since 1957 (Figure 5b4). Therefore, increasing trends in the frequency of CHDE are found over forest

FIGURE 6 Trends (per decade) in the frequency of dry compound extremes (d1-d3) and hot compound extremes (h1-h3) of different magnitudes over four different land cover types. I (1), II (2) and III (3) present mildly, moderately and severely dry (hot) conditions. F, C, G and U are for forest, cropland, grassland and urban. Numbers in the brackets present the average trends in the frequency of DCHDE and NCHDE of all stations over different land cover types. Error bars denote *SE*

with the highest frequency of CHDE in the recent decade after 2010, whereas the frequency of DCHDE has decreased but that of NCHDE has increased over urban.

Dry CHDEs of different dry magnitudes have generally increased over four land covers with the largest increasing trend over forest, except for DCHDE_III, which has decreased over four land covers except over grassland (Figure 6d1-d3). DCHDE_II and NCHDE_II suggest the second-largest increasing trend over urban next to forest (Figure 6d2). For hot CHDEs, DCHDEs of different hot magnitudes indicates the largest increasing trends over grassland, whereas, the largest increasing trends of NCHDE_1 and NCHDE_2 are detected over forest and that of NCHDE_3 are detected over grassland (Figure 6h1-h3). Moreover, increasing trends in day-time hot CHDEs are larger over grassland than cropland whereas those in night-time hot ones are generally similar over grassland and cropland. In general, larger increasing trends of CHDE of different dry and hot magnitudes are mainly detected over forest and grassland.

3.4 | Discussions

Generally, the larger increasing trend in NCHDE than DCHDE is attributed to the significant ($p < 0.05$) larger increasing trend in daily minimum (0.32°C 10a^{-1}) than maximum (0.19°C 10a^{-1}) temperature (Figure 7a,b). Also, larger increasing trends in temperatures in north China may shape the spatial pattern that more stations have experienced increasing trends of CHDE in north China (Figure 7a,b).

For hot or dry CHDEs (DCHDE and NCHDE), the 62-year average frequency and trend in the frequency of dry CHDE decrease with the increasing dry severity (I > II > III) (Figures 8d1-d6 and 9). However, that of moderately hot CHDE is the highest of all hot ones (2 > 1 and 3) (Figures 8h1-h6 and 10). The declining frequency of dry CHDE with increasing dry magnitudes is largely determined by the declining frequency of drought from mild, moderate to severe (D_I > D_II > D_III) (Figure 11a). The highest frequency and largest

FIGURE 7 Trends (per decade) in maximum (a, TX), minimum temperatures (b, TN), precipitation (c, Prep) and SPI (3) (d) of 303 stations across China from 1957 to 2018. Numbers in the brackets present trends averaged from 303 stations

increasing trends in moderately hot CHDE are consistent with the highest frequency and largest increasing trends in moderate heatwaves (DHW_2 and NHW_2) (Figure 11a,b). Therefore, the likelihood of CHDEs of different hot or day magnitudes is largely determined by the likelihood of heatwave or drought defined by the prescribed thresholds. In combination with the larger increasing trend in NCHDE than DCHDE, increasing trends in NCHDE_I (0.07 per decade) and NCHDE_2 (0.06 per decade) are the largest among all dry and hot ones (Figures 9b1 and 10b2). Temporally, a transition from decreasing to increasing trend is also detected in hot and dry DCHDEs, and a generally significant ($p < 0.05$) increasing trend is detected in hot and dry NCHDEs in recent decades since the 1990s. The spatial extent of increasing trends in dry CHDE has narrowed with the increasing dry severity (I > II > III) (Figure 9), whereas that in hot CHDE has expanded with the warming magnitude (1 < 2 < 3) (Figure 10).

Based on trends in maximum, minimum temperatures, precipitation and SPI (3) of 303 stations (Figure 7a-d), apart from the warming and wetting trend in northwest China, both north and south China have experienced a general warming and drying trend, in which, north China experiences stronger warming trend and south China indicates stronger drying trends. Strong drying trends in south China may increase the probability of drought, which contributes to the increasing trends in CHDE over the humid and sub-humid regions under the warming context. In contrast, over the arid region, the decrease of CHDEs of different dry magnitudes is largely caused by the warming and wetting trend in this region since the wetting trend may reduce the probability of drought. Risks of moderately and severely dry ones and mildly hot ones have been relieved over this region. This warming and wetting trend in northwest China has been reported in the previous study (Li *et al.*, 2016; Peng and Zhou, 2017). Over the semi-arid region, the general large increasing trends in CHDE is consistent with the warming and drying trend during the past 62 years. In general, there is a good agreement between changes in CHDE and regional climate change over different regions.

According to trends in DHW, NHW and droughts over four land covers (Figure 12a–c), larger increasing trends of NCHDE over forest are contributed by the larger increasing trends in NHW. The smallest decreasing trend in drought over forest would accordingly keep the

FIGURE 8 MK test (UF and UB, the primary vertical axis) and temporal variations (column charts, the secondary vertical axis) of day- and night-time compound extremes (DCHDE and NCHDE) of different dry (d1-d6) and hot (h1-h6) magnitudes averaged from 303 stations from 1957 to 2018. I (1), II (2) and III (3) present mildly, moderately and severely dry (hot) conditions. Numbers in the brackets present the average frequency of 303 stations

probability of CHDE from dropping dramatically given the same probability of heatwaves compared to the other three land covers. In contrast, larger increasing trends of CHDE over grassland particularly the largest increasing trends in hot DCHDEs of different magnitudes, are largely influenced by the largest increasing trends in heatwaves (DHW) (Figure 12a–c). Since sensible heat is higher than latent heat over grassland, maximum temperature changes quickly over grassland (Feng and Zhao, 2015), contributing to larger increasing trends of DHW and DCHDE over grassland. Moreover, increasing trends in DCHDE and NCHDE over forest in the recent decade after 2000 may increase the risks of tree mortality (Anderegg *et al*., 2013) and forest fires just like the catastrophic Australia wildfires occurring in 2019 due to the extremely high temperature and drought stress. Also, heatwaves caused by high temperatures over urban (known as urban heat island) persisting for several days may negatively influence human health (Tan *et al*., 2010). If night-time temperatures do not drop, extreme heat can be a killer. Therefore, increasing trends in NCHDE over urban may put humans under severe health risks.

In this study, we have offered some insights into the long-term spatial and temporal changes of CHDE over different regions with different hot and dry conditions as well as different land cover types over China. Some limitations can be further improved in future work, for example,

FIGURE 9 Spatial trends (per decade) in day- (a1-a3) and night-time (b1-b3) compound extremes (DCHDE and NCHDE) of different dry magnitudes of 303 stations in China from 1957 to 2018. Numbers in the brackets present the average trends in the frequency of DCHDE and NCHDE of 303 stations. I, II and III present mildly, moderately and severely dry conditions

FIGURE 10 Spatial trends (per decade) in day- (a1-a3) and night-time (b1-b3) compound extremes (DCHDE and NCHDE) of 303 stations in China from 1957 to 2018. Numbers in the brackets present the average trends in the frequency of DCHDE and NCHDE of 303 stations; 1, 2 and 3 present mildly, moderately and severely hot conditions

FIGURE 11 The 62-year average frequency (a) and trends (b) of day- and night-time heatwaves (DHW and NHW) and droughts (D) averaged from 303 stations over China from 1957 to 2018. I (1), II (2) and III (3) present droughts and heatwaves of different dry (hot) magnitudes from mild, moderate to severe. Error bars denote *SE*

FIGURE 12 Trends (per decade) in the frequency of day- and night-time heatwaves (DHW and NHW) and droughts (D) averaged from all stations over different land cover types from 1957 to 2018. I (1), II (2) and III (3) present droughts and heatwaves of different dry (hot) magnitudes from mild, moderate to severe. F, C, G and U are for forest, cropland, grassland and urban. Error bars denote *SE*

instead of using only SPI for drought indicator, other indicators more applicable to humid, non-humid, arid and semi-arid regions (Zhang and He, 2016; Zhang *et al.*, 2019) can also be considered. Future efforts are also needed to explore the substantial driving mechanism of these differences over different regions and land covers from the perspective of energy balance and climate change.

4 | CONCLUSIONS

In this study, we investigated the long-term spatial and temporal differences of CHDE over the humid, sub-humid, semi-arid, arid regions and four land covers including forest, cropland, grassland and urban across China from 1957 to 2018. Major findings are summarized as follows.

The 62-year average frequency of day-time CHDEs (1.76) is higher than that of night-time ones (1.39) across China. Both day- and night-time CHDEs have increased in China with a more rapid (2.6 times) and significant ($p < 0.05$) increasing trend in night-time ones in recent decades since the 1990s. Increasing trends in mildly dry night-time (NCHDE_I, 0.07 per decade) and moderately hot night-time CHDE (NCHDE_2, 0.06 per decade) are the largest among all dry and hot CHDEs.

Over four regions, the 62-year average frequency of day- and night-time CHDEs is the highest over the sub-humid and humid regions but the lowest over the arid region. Both day- and night-time CHDEs have increased over the humid, sub-humid and semi-arid regions in the recent decade. Decreasing CHDE over the arid region since 1957 is largely attributed to the wetting trend over this region. Moreover, the frequency of CHDEs of different dry magnitudes has generally decreased over the arid region but increased over the humid region. Increasing trends in CHDEs of different hot magnitudes are generally larger over the semi-arid and sub-humid regions. Increasing trends of CHDEs of different dry and hot magnitudes are generally detected over the semi-arid and sub-humid regions.

Over four land cover types, the 62-year average frequency of day- and night-time CHDEs is the highest over forest but the lowest over grassland. Both day- and night-time CHDEs have significantly ($p < 0.05$) increased over forest after 2010, which may increase the risks of tree mortality and forest fires. The largest increasing trends in the day-time CHDEs of different hot magnitudes over grassland are contributed by the largest increasing trend of day-time heatwaves over grassland. Also, larger increasing trends in night-time CHDE over urban may negatively influence human health.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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