A standardized index for assessing sub-monthly compound dry and hot conditions~~:~~ with application in China

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Abstract: Compound dry and ~~-~~hot conditions ~~pose~~ frequently cause large impacts on ecosystems and societies~~y~~ worldwide. A suite of indices ~~are~~ are available~~proposed~~ for the assessment~~s~~ of droughts and heatwaves~~ previously~~, yet there is no index available for incorporating the joint variability of dry and hot conditions at sub-monthly scale. Here~~,~~ we introduce~~d~~ a daily-scale index, ~~termed as~~called the standardized compound drought and heat index (SCDHI), to ~~measure~~ assess ~~the intensity of~~ compound dry~~ and~~ -hot conditions. The SCDHI is based on ~~the~~ a daily drought index (the standardized antecedent precipitation evapotranspiration index (SAPEI))~~ and~~, the daily-scale standardized temperature index (STI) and a joint probability distribution method. The new index ~~is wa~~is verified against real-world compound dry and hot events and ~~the~~ associated~~related~~ observed vegetation impacts in China. The SCDHI can~~-~~not only capture compound dry and hot events at both monthly and sub-monthly scales, but is also a good indicator for associated vegetation impacts. ~~SCDHI can not only monitor the long-term compound dry and hot events, but also capture such events at sub-monthly scale and reflect the related vegetation activity impacts.~~ Using the SCDHI, we quantify the mean frequency, severity, duration and intensity of compound dry-hot events during the historical period in China and assess the ability of climate models to reproduce these characteristics. We find that the compound events whose severity is at least light and which last longer than two weeks generally persisted for ~~25~~20-35 days in China. ~~; and the s~~Southern China ~~suffers~~ suffered from compound events most frequently, and the most severe compound events were mainly detected in this region. Climate models generally overestimate the frequency, duration, severity and intensity of compound events in China, especially for western regions, which can be attributed to a too strong dependence between the SAPEI and STI in those models. ~~SCDHI index can~~ The SCDHI provides a new tool to quantify sub-monthly characteristics of

compound dry and hot events~~,~~ and ~~conducive~~ to ~~the timely~~ monitor~~ing of~~ their initiation, development, and decay. ~~which~~ This is important information~~are vital~~ for decision-makers and stake~~-~~holders to release early and timely warnings.

Keywords: compound event; SCDHI; SAPEI; sub-monthly scale; China

1 Introduction

Compound dry-~~-~~hot events are climate events during which dry and hot conditions occur simultaneously~~. Compound dry-hot event~~, and such events have been observed ~~for~~ on all continents in recent decades (Hao et al., 2019; Mazdiyasni and AghaKouchak, 2015; Manning et al., 2019; Sutanto et al., 2020). ~~The frequent c~~Compound dry-hot events ~~have~~ can lead to more devastating impacts on natural ecosystems and human society ~~than~~ compared to droughts and heatwaves alone~~individual events~~ (Zscheischler et al., 2014~~, 2018~~; Chen et al., 2019; Hao et al., 2018a). For example, Russia was simultaneously struck by a severe drought and unpresented temperature extremes in the summer of 2010, which caused large-scale crop failures, wildfires, and human mortality (Zscheischler et al., 2018). ~~Unfortunately, the extreme droughts and hots~~ Droughts and heatwaves are expected to occur more frequently in the coming decades under global warming, which potentially results in more compound events in many parts of the world, especially for wet and humid regions (Wu et al., 2020; Swain et al., 2018, Zscheischler and Seneviratne, 2017~~a~~). Therefore, understanding such events ~~are~~is of crucial importance to provide ~~the most fundamental~~relevant information ~~to help~~for disaster mitigation.

~~Much effort has been made to study the~~Many studies have investigated multivariate compound events in recent years (Zscheischler et al., 2020; Ridder et a., 2020). Utilizing ~~different~~ thresholds to define ~~the~~ concurrent climate extremes for a specific period, particularly the frequency of multivariate compound events has received ~~a great deal of~~a lot of attention (Wu et al., 2019; Zhang et al., 2019; Ridder et al., 2020). However, for impacts,~~. Although this approach can detect compound event occurrence, it the method of frequency analysis~~ other ~~fails to quantitatively measure~~ compound event characteristics such as duration, severity, and intensity may be at least as important~~,~~ and may help ~~is inconvenient for comparison of~~to compare compound event characteristics ~~through~~ across different climates (Wu et al., 2020). ~~Therefore, t~~To overcome these ~~shortages~~limitations, several joint climate extreme indices have been proposed for analyzing ~~the~~ characteristics of ~~the~~ compound events beyond frequency. ~~Specifically~~For instance, the standardized dry and hot index based on the ratio of the marginal probability distribution functions of precipitation and temperature was proposed to measure the extremeness ~~degree~~ of a compound drought and hot ~~extreme~~ event (Hao et al., 2018). Hao et al. (2019, 2020) recently proposed the standardized compound event indicator and compound dry-hot index to assess the severity of compound dry and hot events by ~~jointing~~linking the marginal distribution of standardized precipitation index (SPI) and standardized temperature index (STI) using ~~the~~ copula theory. These two joint indices provide useful tools to improve our understanding of the frequency, spatial extent and severity of ~~the~~ compound dry-hot events. ~~However, they are inevitably subjected to some shortcomings including the fixed monthly scale and the disregard of evapotranspiration, which may limit their use in monitoring the detailed evolution of compound dry and hot events.~~

~~With the occurrence of extreme climate (e.g. high temperature, low humidity, and sunny skies), droughts can evolve rapidly(Koster et al., 2019; Otkin et al., 2018; Yuan et al., 2019; Li et al., 2020a). Such extreme weather can appear within a short period without resulting in long-lasting compound events, but rather, short-term droughts and~~

~~heatwaves lasting a few weeks or even days (Mo and Lettenmaier, 2016; Zhang et al., 2019). Severe concurrent drought and heat can suddenly strike a region with a relatively short duration when extreme weather anomalies persist over the same region (Röthlisberger and Martius, 2019; Wang et al., 2016). Concurrent~~ However, when extreme weather conditions (e.g., high temperature, low humidity, and sunny skies) occur within a short period, droughts can evolve rapidly~~,~~ in conjunction with heatwaves (Koster et al., 2019; Otkin et al., 2018; Pendergrass et al. 2020; Yuan et al., 2019; Li et al., 2020a). Despite their short duration, concurrent short-term drought and hot extremes can pose ~~greater potential~~ large socio-economic risks because the combination of ~~these~~ both hazards ~~events~~ can exacerbate their respective environmental and societal impacts (Kirono et al., 2017; Schumacher et al., 2019; Sedlmeier et al., 2018). ~~Specifically,~~For instance, even short-term concurrent dry and hot extremes can lead to significant agricultural loss if they occur within sensitive stages in crop development such as emergence, pollination, and grain filling (Haqiqi et al., 2021; Luan and Vico et al., 2021; Zhang et al., 2019). Under climate change, short-term concurrent dry and hot extremes are expected to increase (especially for humid regions), potentially causing substantial damage to natural ecosystems and society (Li et al., 2020b; Sun et al., 2019). To improve understanding of such short-term compound events and ~~make~~ issue early and timely warnings, decision-makers and stakeholders require more detailed information such as the start time, severity, and the projected ~~projected~~ tendency ~~in~~ for the coming days rather than the average state at a fixed monthly scale (Pendergrass et al., 2020). However, the above-mentioned indices often only allow for identifying compound dry-hot events at a relatively coarse (i.e., the monthly) temporal resolution (Hao et al., 2019, 2020)~~.~~ and key characteristics of climate extremes may not be detectable at monthly scale (Lu, 2019; Lu et al., 2014; Otkin et al., 2018). For instance, hot extremes generally occur at much finer time scales (e.g., days and weeks) (Zhang et al., 2019). ~~Correspondingly~~Consequently, sub_-monthly-~~-~~scale indices for characterizing short-term compound dry and hot ~~events~~ conditions are needed. In addition, through the influence of evapotranspiration, ~~short-term~~other meteorological variables that vary at short time scales (e.g., relative humidity, wind speed, and radiation~~temperature and radiation~~) ~~are considered an important factor in~~may be important drivers of drought and heatwave concurrences (James et al., 2010). Thus, the development of a compound drought and heat index should consider other important ~~drought/hot-related factors including temperature and~~ variables such as evapotranspiration.

~~The complexity of compound events makes it an unusual task to develop a simple and robust index to quantify their past and future changes (Zscheischler et al., 2020). A suite of indices are proposed for the assessments of droughts and heatwaves previously, yet there is no index available for incorporating the joint variability of dry and hot conditions at sub-monthly scale.~~ Here we ~~aim to formulate~~develop a compound drought and heat index, called the standardized compound drought and heat index (SCDHI), for monitoring ~~and analyzing~~ compound dry and hot events at sub-monthly scale. To achieve this aim, we combine a daily scale drought index, the standardized antecedent precipitation evapotranspiration index (SAPEI), which simultaneously considers precipitation and potential evapotranspiration, with a daily-~~-~~scale standardized temperature index (STI). The SCDHI provides a new tool to quantify various characteristics of compound dry-hot events~~,~~ and can be computed at multiple time scale (e.g., daily, weekly and monthly).

Several studies have been carried out to study compound dry-hot event in China (Chen et al., 2019; Hao et al., 2019; Wu et al., 2020; Zhang et al., 2019; Zhou and Liu, 2018), and these studies help to better understand such events. However, they mostly focused on the frequency and severity of the compound dry-hot event at a relatively coarse (i.e., the monthly) temporal resolution without considering their duration and intensity. ~~In addition, the impact of climate change on compound dry-hot event and its future change in China remains unclear.~~In addition, the effect of climate model bias on the characteristics of compound dry-hot event in China remains unclear. Understanding climate model biases is a crucial step to assess the risk of future compound dry-hot events (Villalobos-Herrera et al., 2020). Recent compound dry-hot events have resulted in serious social and economic losses in China (Wu et al., 2020; Zhang et al., 2019), motivating further study of these potentially very damaging events. Using the SCDHI, here we investigate important~~the~~ characteristics such as frequency, duration, severity, and intensity of compound dry-hot event~~s~~ during the historical (1961-2018) period and evaluate the effect of climate model biases on compound event characteristics in China.~~project their changes in China for the future (2050-2100) under different emission scenarios. This index can provide a new tool to quantify the characteristics of compound dry-hot event, and can monitor the compound dry-hot event at multiple time scale (e.g., daily, weekly and monthly) to provide detailed information on their initiation, development, decay, and trends.~~

The paper is organized as follows: Section 2 introduces the data used in this study, the development of SCDHI. In the Section 3, the validation of SAPEI and SCDHI are presented and characteristics of compound dry-hot event and the impact of climate model bias on its characteristic are investigated. The study is concluded in Section 4.

2. Data and methodology~~Methods~~

2.1 ~~data~~Data

Daily meteorological datasets covering 1961 to 2018 were collected from 2239 observational stations across the non-arid region in China (Fig. 1), which include precipitation, maximum air temperature, mean air temperature, minimum air temperature, relatively humidity, wind speed, and sunshine duration. ~~All of these meteorological~~The data with strict quality control are available from the China Meteorological Administration (http://cdc.nmic.cn/home.do) and the Resources and Environmental Science Data Center, Chinese Academy of Sciences (http://www.resdc.cn/Default.aspx). The observational station data were interpolated to 0.25× 0.25° gridded data by kriging~~ method~~, as it yields higher interpolation accuracy than the other commonly used methods, e.g., ordinary nearest neighbor and inverse distance weighting (Liu et al., 2016). In this study, we only focus the non-arid region in China, because of three reasons: (1) replenishment of water resources across the Chinese arid region is mainly from melted glacial or perennially frozen soil, but not from precipitation; (2) meteorological observations in the arid regions of China~~Chinese arid regions~~ are too scarce to conduct robust analysis (Wu et al., 2007; Xu et al., 2015); (3) from a practical perspective, calculating climate extreme indices across arid region ~~with large-scale~~and desert~~-regions~~s is less meaningful~~less~~ (Tomas-Burguera et al., 2020).

~~The two commonly used indices (i.e., monthly Palmer drought severity index (PDSI) and standardized precipitation evapotranspiration index (SPEI) were employed for comparison. PDSI and SPEI were computed from the same meteorological data described above. The conventional PDSI was empirically derived using the meteorological data of the central USA with its semi-arid climate. The portability of the conventional PDSI is thus relatively poor (Liu et al., 2017). In this study, PDSI was calculated according to the China national standard of classification of meteorological drought with standard number of GB/T 20481-2017. The PDSI was built based on long-term meteorological data of in-situ stations evenly distributed around China, hence well~~

~~monitor drought in China (Zhong et al., 2019a), and the detailed calculation on the PDSI is shown in supplementary materials.~~ The 0.25°-daily root zone (0 - 100 cm) soil moisture dataset obtained from the Community Land Model of the Global Land Data Assimilation System (Li et al., 2018; Rodell et al., 2004) was also used in this study. The Community Land Model product does not have explicit vertical levels, instead soil moisture is represented in surface (0-2cm), and root zone soil moisture (0-100cm) (Li et al., 2018). Root zone soil moisture is chosen over the surface soil moisture on account of its appropriateness~~ositeness~~ to characterize drought and~~,~~ lower noise relative to surface soil moisture (Hunt et al., 2009; Osman et al., 2020). The dataset from 1961 to 2014 were downloaded from the Goddard Earth Sciences Data and Information Services Center (https://earthdata.nasa.gov/eosdis/daacs/gesdisc~~Rodell et al., 2004~~). The soil moisture dataset from the Community Land Model ~~can well~~ captures dry and wet conditions in China well (Bi et al., 2016; Feng et al., 2016). To avoid the effect of seasonality, ~~the~~ soil moisture was fitted by a Gamma ~~probability~~ distribution~~,~~ and ~~then was~~ subsequently standardized by normal quantile transformation (Herr and Krzysztofowicz, 2005). In addition, 8-day leaf area index of the MOD15A2H from 2003 to 2018 were collected. ~~These data were~~After ~~resampled~~ resampling to a 0.25° spatial resolution, we subtracted the local mean and divided by the local standard deviation~~, and then the Z-score was used~~ to ~~calculate the~~obtain normalized leaf area index anomalies.

We further used ~~eight~~ global climate models~~s~~ from the Coupled Model Intercomparison Project Phase 5 (https://esgf.llnl.gov/) to assess the effect of climate model biases on compound dry-hot events ~~(Taylor et al., 2012),~~ (Taylor et al., 2012). ~~including~~ The global climate models used in this study include CanESM2, CNRM-CM5, CSIRO-Mk3.6, MIROC-ESM, MPI-ESM-LR, BCC-CSM1-1, IPSL-CM5A-LR, and MRI-CGCM3.~~, were used to project the future climate conditions.~~ These ~~global climate~~ models exhibit good performance ~~to~~ in their ~~simulate~~ simulation of ~~the~~ key features of precipitation and temperature in China (Jiang et al., 2016; Yang et al., 2019). We obtained daily climate variables (e.g., precipitation, temperature, relatively humidity, and wind speed) for the historical (1961-2005)~~future (2050-2100)~~ periods. ~~for the three Representative Concentration Pathways (RCPs) including RCP 2.6 (low emission scenario), RCP 4.5 (moderate emission scenario) and RCP 8.5 (high emission scenario).~~ All of the global climate models' outputs were based on the first ensemble member of each model. ~~, referred to as *r1i1p1* in all of the experiments.~~ In this study, the bias-corrected climate imprint method, one of the delta statistical downscaling methods, was used to downscale the global climate models outputs to a spatial resolution of 0.25° (Werner and Cannon, 2016). The detailed information on these global climate models is shown in Table S1.

2.2 Development of SCDHI

The SCDHI is a compound drought and heat index based on a daily drought index and the STI~~.~~, both of which are briefly introduced in the following.~~, which is computed in a similar fashion as the Standardized Precipitation Index (Zscheischler et al., 2014). The calculation of daily STI is similar to monthly STI, but for standardizing daily temperature. For example, with respect to one certain grid point, the 1 January STI are computed on the 1 January temperature datasets observed during 1961-2018 at each grid point. We firstly formulatedThe STI and a daily scale drought index, i.e., the SAPEI will be quickly introduced in the following.i.e. the SAPEI, by considering both precipitation and potential evapotranspiration. The Penman-Monteith method is used to calculate the potential evapotranspiration. Afterward, the~~ Afterwards, we will explain how the joint distribution method was employed to compute the SCDHI from the two univariate indices.

2.2.1 Formulation of daily-scale drought and heat ~~index~~indices

~~Li et al. (2020b) have proposed the daily-scale drought index (SAPEI) that considers both precipitation and potential evapotranspiration. H~~The daily-scale drought index (SAPEI) was first introduced by Li et al. (2020b). However, the primary limitation of this index is that it has a fixed temporal scale (the number of considered antecedent days was equal to 100) and cannot reflect ~~the~~ dry and wet condition at different time scales. Given that drought is a multi-scalar phenomenon (Mckee et al., 1993, Vicente-Serrano et al., 2010), here we extended the SAPEI to a multiple time scale (i.e., 3-, 6-, 9-, and 12-month) daily drought index.~~ Hence, we developed the multiple time scale (i.e., 3-, 6-, 9-, and 12-month) daily drought index.Hence, in this study, we developed the multiple time scale (i.e., 3-, 6-, 9-, and 12-month) daily drought index. Here, we followed the same nomenclature proposed by Li et al. (2020b) to refer to a daily standardized drought index (SAPEI) based on precipitation and potential evapotranspiration. SAPEI is simple to calculate, and uses the antecedent accumulative differences between precipitation and potential evapotranspiration to represent the dry and wet condition of the current day. The calculation procedure is described below.~~

The Penman-Monteith method (Allen et al., 1998) was ~~firstly~~ used to compute potential evapotranspiration. ~~With a value for potential evapotranspiration, t~~The daily difference between precipitation and potential evapotranspiration was then calculated to ~~reveal~~ estimate ~~climatic~~ the water balance.~~ (precipitation minus potential evapotranspiration).~~ To reflect dry and wet conditions of ~~the~~ a given day, the antecedent water surplus or deficit (WSD) was calculated through the following equation~~s~~:

$$WSD = \sum_{i=1}^{n} \left(P - PET\right)_i \qquad (1)$$

w~~W~~here n is the number of previous days, PET represents the potential evapotranspiration, and P represents precipitation.

The WSD values can be aggregated at different time scales, such as 3, 6, 9 months, and so on. The daily WSD series was fit to a log-logistic distribution. Subsequently, cumulative probabilities of the WSD series were obtained and transformed to standardized units using the classical approach of Barton et al. (1965), resulting in the SAPEI.

The STI was computed in a similar fashion as the SPI, while it did not accumulate temperature in a fixed scale. The calculation of daily STI relied on daily temperature. A normal distribution was fitted to daily temperature at each day of the year, because temperature anomalies can be assumed to be normally distributed (Hansen et al., 2012; Zscheischler et al., 2014). The STI was then computed based on the cumulative distribution function *G(x)*, that is, are listed below:

$$G(x) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{x} \exp(-\frac{(x-\mu)^2}{2\sigma^2}) dx \qquad (2)$$

$$STI = \varphi^{-1}(q) \qquad (3)$$

where x is temperature time series. x and σ are the mean and standard deviation parameters, respectively. q is the cumulative probability and φ is the standard normal distribution.

~~A probability distribution was used to fit the daily time series WSD. Given that different probability distributions may cause differences in drought indices (Stagge et al., 2015), to select the most suitable distribution, several commonly probability distributions~~

~~including the general extreme value, log-logistic, lognormal, Pearson III, generalized Pareto, exponential, and normal distributions, should be used to fit the WSD series. In the study of Li et al. (2020b), Shapiro-Wilk and Kolmogorov-Smirnov test have been used applied for optimal probability distribution selection by comparing the empirical probability distribution with a candidate theoretical probability distribution. They suggested that the log-logistic distribution is more suitable for SAPEI. Moreover, previous researches have demonstrated that the log-logistic distribution is suitable for standardizing drought indices, e.g. SPEI (Vicente-Serrano et al., 2010). Therefore, we chose the log-logistic distribution to compute SAPEI. Once the daily WSD series were fit to a probability distribution, cumulative probabilities of the WSD series were obtained and transformed to standardized units (SAPEI) using the classical approach of Barton et al. (1965).~~

2.2.2 Construction of SCDHI

The SCDHI was established ~~through~~ using copula theory (a brief introduction on copula theory is ~~shown~~ given in supplementary materials), which ~~can~~ essentially ~~combine~~ models the ~~candidate variables into one numerical expression~~dependence between the SAPEI and the STI to generate a bivariate distribution linking the two indices. ~~This approach not only realizes a projection from multiple dimensions to a single dimension, but also the marginal distributions of the candidate variables combined with their original structures can be fully preserved within the constructed joint distribution. Hence, the copula-based index provides an objective description of the compound events (Hao et al., 2018b; Terzi et al., 2019).~~

There are many copula families available, which have widely been used for ~~jointing~~ modelling bivariate distributions (Terzi et al., 2019). Among ~~then~~them, Clayton, Gumbel, Normal, t~~T~~, and Frank copula perform well for ~~jointing~~ bivariate hydrometeorological variables (Ayantobo et al., 2018; Liu et al., 2019), and thus were ~~employed~~ tested to establish the bivariate joint probability distribution in this study. Assuming, the two random ~~Gaussian~~ variables X and Y, representing SAPEI and STI, respectively, the compound dry-hot event can be identified as one variable X ~~lower~~ less than or equal to a threshold x, and the other variable Y higher than a threshold y at the same time. The joint probability p of the compound dry-hot event can then be expressed as:

$$p = P(X \le x, Y \ge y) = u - c(u,v) \qquad (\cancel{2}4)$$

where u and v are~~was~~ the respective thresholds after transforming X and ~~Y~~ to uniform marginal distributions (Ayantobo et al., 2017)~~, respectively~~, and $c(u,v)$ ~~was~~ is the joint probability distribution based on the fitted copula (Zscheischler and Seneviratne, 2017~~a~~).

This joint cumulative probability p ~~could~~ can then be treated as an indicator, where smaller p values denote more severe condition of compound dry-hot ~~event~~conditions. ~~However, p to the given marginal sets, p values in different seasons or areas reflected different conditions and are thus not comparable.~~ However, because the marginal distributions usually vary across seasons and regions, the same value of does not correspond to the same univariate exceedance thresholds across seasons and regions but rather refer to similar bivariate extremeness in the bivariate SAPEI-STI distribution. ~~Hence,~~Transforming the joint probability p ~~was transformed~~in~~-~~to a uniform distribution by fitting a distribution F, and subsequently into a standard normal distribution results in~~which was then standardized as~~ an indicator to characterize compound dry-hot events. ~~Once the P series at each day were fitted to a copula, the P series were transformed to standardized units.~~Hence, the SCDHI ~~can be estimated~~is computed by taking the inverse of the joint cumulative probability (p)~~ as~~:

$$SCDHI = \varphi^{-1}(F(P(X \le x, Y \ge y)))$$ (~~3~~5)

where φ is the standard normal distribution function and~~.~~ F is the marginal cumulative distribution, which remaps the joint probability to the uniform distribution (Yeo and Johnson, 2000).~~the distribution F was estimated based on the Yeo-Johnson transformation formula (Yeo and Johnson, 2000).~~

Following the categories of compound dry and hot conditions as suggested by Wu et al. (2020)~~ (Wu et al., 2020)~~, we define~~d~~ five categories of compound dry and hot conditions, including abnormal, light, moderate, heavy and extreme compound ~~drought~~dry-hot, as shown in Table 1. The development of the SCDHI is illustrated in Fig. 2.

~~We used Akaike information criterion, Bayesian information Criterion, and Kolmogorov-Smirnov statistics as goodness-of-fit measures to select an appropriate copula. These statistical measures have been commonly used for estimating the goodness-of-fit of a proposed cumulative distribution function to a given empirical distribution function (Liu et al., 2019; Terzi et al., 2019). The statistics of the three metrics are presented in Fig. S1-3. According to the evaluation metrics, the Frank copula was utilized to establish the joint probability function and construct SCDHI in this study. Note that the SCDHI under three future scenarios is also used the Frank copula, while the parameters are assessed by future scenarios data. The SCDHI~~

~~development was illustrated in Fig. S4.~~

~~Furthermore, to verify the ability of SCDHI to capture the compound dry and hot event, three verification metrics were used (i.e., probability of detection, false alarm ratio, and critical success index) (Winston and Ruthi, 1986).~~

~~$\textit{Probability of detection} = hit/(hit + miss) \quad (4)$~~

~~$\textit{False alarm ratio} = \textit{false alarm} / (hit + \textit{false alarm}) \quad (5)$~~

~~$\textit{Critical success index} = hit / (hit + \textit{false alarm} + miss) \quad (6)$~~

~~where *hit* (observed drought-hot) refers to the number of grids when SAPEI and STI is subjected to grade 1-4 and SCDHI is subjected to grade 1-4; *Miss* denotes the number of grids when SAPEI and STI is between grade 1-4 and SCDHI is subjected to other grades than grade 1-4; *False alarm* denotes the number of grids when SAPEI and STI is subjected to other grades than grade 1-4 but SCDHI is subjected to grades of grade 1-4.~~

2.2.3 Evaluation metrics

We used the Akaike information criterion (AIC), Bayesian information Criterion (BIC), and Kolmogorov-Smirnov (KS) statistics to select the most appropriate copula. The KS test indicates the goodness-of-fit between the empirical and theoretical distributions (Wu et al., 2018), while the BIC and AIC are a relative measure of the quality of a model for a given set of data and helps in model selection among a finite set of models (Li et al., 2013). The preferred model is the one with the lower AIC and BIC values but the higher *p* values in the KS test. These statistical measures have been commonly used for selecting appropriate copulas (Zscheischler et al., 2017; Zscheischler and Seneviratne, 2017; Liu et al., 2019; Terzi et al., 2019). The statistics of the three metrics are presented in Fig. S1-3, indicating that the Frank copula showed lower AIC and BIC values but higher *p* values of KS test compared to other copulas. Overall, all test showed comparable results. The Frank copula was thus utilized to model the dependence between SAPEI and STI and to construct the SCDHI as explained in Section 2.2.2. ~~Note that for the SCDHI under three future scenarios we also used the Frank copula, refitting the parameters to the data from the climate model projections.~~

2.3 Other drought indicators

The two commonly used drought indices monthly Palmer drought severity index (PDSI) and standardized precipitation evapotranspiration index (SPEI) were employed for comparison against SAPEI. The conventional PDSI was empirically derived using the meteorological data of the central USA with its semi-arid climate. The portability of the conventional PDSI to other world regions is thus relatively poor (Liu et al., 2017). In this study, PDSI was calculated according to the China national standard of classification of meteorological drought with standard number of GB/T 20481-2017. The PDSI was built based on long-term meteorological data of in-situ stations evenly distributed around China (Zhong et al., 2019a). The detailed calculation on the PDSI and SPEI are presented in the supplementary materials.

2.4 Run theory to extract compound event characteristics

Run theory (Yevjevich and Ingenieur, 1967) was used to identify the frequency, duration, severity, and intensity of compound dry-hot events. A ‘run’ is defined as a portion of the time series of a variable X_t, in which all values are either below (i.e., negative run) or above (i.e., positive run) a selected truncation level of X_0 (Ayantobo et al., 2017). Figure~~.~~ 3 illustrates an example with two compound dry-hot events, and each compound dry-hot event is characterized by its respective duration, severity, intensity, and non-compound dry-hot condition. Specifically, according to the truncation level X_0, the number of consecutive intervals (days) where values remain below X_0 defines *duration*, while the cumulative sum of values during a compound dry-hot period and the minimum value within a compound dry-hot period defines *severity* and *intensity*, respectively. *Frequency* is simply the number of events in the given time period. Duration and severity are thus defined as~~:~~

$$duration = t_e - t_i \qquad (12)$$

$$severity = \sum_{t=1}^{D} SCDHI_t \qquad (13)$$

where t_e is terminate time, t_i is initiation time, D is duration. In this study, X_0 was set to -0.8, -1.3, and -1.6 to assess the characteristics of compound dry-hot events under different thresholds. Furthermore, for the assessment of compound event characteristics in this study, events shorter than two weeks were discarded.

3 Results and ~~Discussion~~discussion

3.1 Evaluation of SAPEI

The SCDHI was established based on the daily STI and the daily~~-scale~~ drought index~~, i.e.,~~ SAPEI. However, no previous studies have tested the daily drought monitoring performance of the SAPEI at multiple time scales. ~~When developing a drought index, rigorous testing is required with respect to its applicability before it is applied in drought monitoring.~~ Figure~~.~~ ~~2~~ 4 shows the spatial distributions and probability ~~density~~ densities of the correlations between SAPEI and SPEI/PDSI/soil moisture across China. The monthly mean SAPEI at 3-, 6-, 9- and 12-month scale all ~~showed~~ shows strong agreement with the SPEI in China, and ~~, with~~ correlation coefficients were typically higher than 0.8 ~~(p < 0.01)~~, indicating that the monthly SAPEI at multiple time scale calculated from ~~the~~ daily values ~~could have the same~~has similar capability to monitor monthly drought as SPEI. ~~of monthly drought monitoring as SPEI.~~ The 3-, 6-, 9- and 12-month SAPEI also generally showed ~~good~~ high correlations with the PDSI, ~~and~~ in particular the 3-month SAPEI and PDSI are well~~generally~~ correlated ~~closely~~, with correlation coefficients higher than 0.6 ~~(p < 0.01)~~. For the daily SAPEI at 12-month scale and soil moisture, a close correlation was detected in south and north China, while relatively weak correlation ~~is~~ was found in Midwest China. The correlation between SAPEI and soil moisture increased in magnitude at time scales of 3 to ~~-~~9 months. For the 12-month SAPEI, mean correlation coefficient reached about 0.5 for ~~whole~~ all of China. The~~i~~se ~~phenomenon implied~~results indicate that the short-time scale SAPEI ~~was~~ is more sensitive to precipitation ~~change~~variability, and thus could be more suitable for meteorological drought, while the long-time scale (more than five month) SAPEI ~~was~~ is more closely related to soil moisture and can thus be applied for agricultural drought monitoring. Overall, these analyses indicate that the SAPEI at daily and monthly scale ~~showed reliability~~is a reliable indicator ~~in~~ for drought monitoring at different time scales.

To further test the drought monitoring performance of the SAPEI, typical drought events were chosen as case studies. ~~During recent decades, several well-known large-scale drought events have hit China, including the droughts in winter of 2009 to spring of 2010, and in 2011 (Lu et al., 2014; Yu et al., 2019). In this study, the drought regimes during these events were taken as case studies to evaluate the drought monitoring performance of SAPEI at 3-month time scales (Sun and Yang, 2012).~~ We firstly showed the monthly evolution of these events by the monthly mean SAPEI, SPEI, and PDSI, and then analyzed the temporal ~~daily~~ evolution of drought at daily scale ~~in space and~~

~~time~~ in the most affected areas according to SAPEI and soil moisture.

~~**3.2.1 Drought events during 2009-2010**~~

~~As shown in Fig. S5, the monthly evolution in 2009/10 drought based on SAPEI was generally similar with that of SPEI and PDSI. This drought started to appear in most of China (except for the central and northeast China) in September 2009, and then persisted in most of China during October to December 2009. During January and April in 2010, severe drought persisted in southwest China, while drought in the rest of China gradually disappeared in this period. After that, dry conditions in southwest China gradually relieved from May to June in 2010, but did not disappear.~~

Despite being located in the humid climate zone, southwest China suffered from exceptional drought during the autumn of 2009 to the spring of 2010 (Lin et al., 2015). ~~During this drought, more than 16 million people and 11 million livestock faced drinking water shortages, with direct economic losses estimated at 19 billion yuan in southwest China (Lin et al., 2015). We selected this event in southwest China as the first case study, and reveal spatial and temporal change of this event at daily scale based on SAPEI and soil moisture (Fig. 3 and 4).~~ We selected this event in southwest China as the first case study. As shown in Fig. S4, the monthly evolution in 2009/10 drought based on SAPEI was generally similar with that of SPEI and PDSI. Figure 5 reveals the daily change of this event using SAPEI and soil moisture. During the September ~~1 to 30~~ of 2009, the drought started to appear in the region, and dry conditions became worse and spread throughout nearly the entire southwest of China from October 1 to November 15 of 2009. Severe dry conditions then stayed in the region for 152 days from November 15 to April 15 of 2010, with high intensity. Afterwards, severe drought was gradually relieved from April 15 to June 15. The drought diminished over time in most parts of southwest China by the end of June.

~~3.2.2 Drought events in 2011~~

~~As shown in Fig. S6. The 2011 drought monthly pattern monitored by SAPEI are generally consistent with those by SPEI and PDSI. The drought mainly started in north China in January, while in March it spread to most of China, and severe dry conditions persisted in most areas during April to May. In August, the drought mainly moved to southward. Severe drought persisted in southwest China during September and October, but it then gradually faded away. The results monitored by the SAPEI are generally consisted with the findings of Lu et al. (2014).~~

~~The~~ In 2011, a particularly unusual drought event ~~was particularly unusual~~occurred in the middle and lower reaches of the Yangtze River Basin (MLR-YRB). The MLR-YRB is generally in a wet condition.~~;~~ ~~nevertheless~~Nevertheless, it suffered its worst drought in the recent 50 years during the spring 2011. Th~~e severe~~is drought caused shortage of drinking water for 4.2 million people~~.~~ and 3.7 million hectares of crops were damaged or destroyed (Lu et al., 2014; Xu et al., 2015). ~~Moreover, the heavy drought led to more than 1,300 lakes devoid of all water in Hubei province (Xu et al., 2015). The temporal and spatial evolution of this event in MLR-YRB described by daily SAPEI and soil moisture was shown in Fig. 5-6.~~ As shown in Fig. S5, the monthly spatial evolution of the 2011 drought indicated by the SAPEI are broadly similar to those by SPEI and PDSI. The temporal evolution of this event in MLR-YRB described by daily SAPEI and soil moisture is shown in Fig. 6. The drought started to appear in the northern part of the MLR-YRB in early February of 2011, and then gradually expanded to the whole MLR-YRB during early February ~~and~~ until March 15. ~~The~~ ~~s~~Severe drought condition persisted in this region for 78 days (from March 15 to May 31). Afterwards, ~~there was a tendency toward alleviating~~ drought conditions alleviated~~,~~ and most of MLR-YRB ~~was~~ continued to be under light and moderate drought conditions.

Overall, similar to the SPEI, SAPEI includes multiple time scales (3-, 6-, 9-, and 12- month) to monitor drought at monthly resolution and is relatively sensitive to soil moisture variations. However, the SAPEI has the advantage to allow for sub-monthly drought monitoring. Such an index could help fill a gap between science and applications in that it could be operationally used for detecting and monitoring both short-term and persistent droughts.

~~The previous detailed analysis showed that the SAPEI not only captures monthly characteristics of droughts, but also has the potential to track droughts at sub-monthly scale (Li et al., 2020b). Though the input data (including precipitation and potential evapotranspiration) of SAPEI are similar to SPEI, the rationale of the index is different from SPEI. It was calculated for each day and considers the water surplus or deficit of that day and the previous days. SPEI was commonly employed to monitor and analyze the monthly or longer-scale droughts (Vicente-Serrano et al., 2010). It thus may not be appropriate to apply the SPEI at shorter timescales (e.g., daily or weekly), because of the inherent problem in the construction of the index. Although SPEI gives a full and equal consideration to the water surplus or deficit in the period of the considered time scale, it does not consider the water surplus or deficit in the days before the period. If the scale is very short, this may cause problems. For a 7-day period, for example, if there is no precipitation during the period, it may be regarded as a drought period when compared with historical records (the method used by the SPEI); however, if there is a heavy precipitation just before the period, then the 7-day period probably remains wet and is unlikely to experience drought condition during such a short time. Previous studies have demonstrated the disadvantage of SPEI for short-time scale drought monitoring (Lu, 2009; Lu et al., 2014; Li et al., 2020b).~~

~~Soil moisture would be the most appropriate variable for agriculture drought monitoring and analyses (Mishra and Singh, 2010). However, there are few long term and large-scale observational soil moisture datasets due to insufficient observation stations around the world, especially for developing regions, which limits it wide use in drought monitoring and analyses (Seneviratne et al., 2010). Thus, using observational hydrometeorological datasets, the complex physical process models, such as the variable infiltration capacity model, are widely used to simulate the soil moisture (Liang et al., 1996; Xia et al., 2018). However, running such models requires highly trained personnel not usually available at local agencies. In addition, when the model is used locally, it generally needs to be calibrated and verified by observational datasets (Xia et al., 2018; Zhou et al., 2019). This certainly limits the wide use of soil moisture as a drought indicator.~~

~~In summary, the SAPEI meets the requirements of a drought index, given the fact that it shows reliable and robust ability for drought analysis and monitoring. Like the SPEI, SAPEI includes multiple time scales (3-, 6-, 9-, and 12- month) to monitor drought at monthly resolution and is relatively sensitive to soil moisture variation. However, SAPEI has the advantage over SPEI regarding sub-monthly drought monitoring. Such an index could help fill a gap between science and applications in that it would be operationally tractable for detecting and monitoring both short-term and sustained droughts.~~

3.2 Evaluation of the SCDHI

The SCDHI was developed by ~~joining~~ linking the marginal distribution of the SAPEI and STI. Though the copula method has been widely utilized to connect ~~bivariate~~ two dependent distributions, the ~~property~~ ability of the SCDHI to~~in~~ ~~capturing~~ capture compound dry-hot events ~~still~~ needs to be tested. Figure 7 shows the spatial distributions of the correlations between SCDHI and SAPEI/STI at daily scale across China. The SCDHI all showed strong ($p < 0.01$) correlation with the SAPEI at 3-, 6-, 9- and 12-month scale in China, with correlation coefficients higher than 0.7. A significant correlation ($p < 0.01$) was also detected between STI and SCDHI at multiple scales.~~Fig. 7 shows the spatial pattern and density for probability of detection, false alarm ratio, and critical success index when the drought and hot events observed identified by the SAPEI and STI, respectively were related toin relation to compound drought-hot events detected by SCDHI at 3-, 6-, 9- and 12-monthly scale. As shown in Fig. 7, pProbability of detection is close to 1 and false alarm ratio is close to 0, implying that SCDHI can well detect in most of the areas where the droughts and hot extremess were detected by SAPEI and STI. The values of the critical success index indicated that the ratioos of drought-hot affected areas locations where compound droughts and hot extremes were detected by SAPEI and STI to the ones drought and hot areas detected by the SCDHI were close to one.~~ Hence, overall the SCDHI is well correlated with univariate variations in drought and heatwave occurrence.~~Overall, these analyses implied that SCDHI can well monitor droughts and hots that can be successfully~~. ~~captured by SAPEI and STI. The SCDHI thus detects compound dry-hot events that are identified separately by the coincidence of low SAPEI and high STI. In addition, the SCDHI detects events that are very extreme in either the SAPEI or the STI can and moderate in the other variable but thus still cause substantial damage (Zscheischler et al., 2017b). Furthermore, as a univariate indicator, the SCDHI is able to quantify the magnitude of compound dry-hot events.~~

To further test the drought-heat monitoring performance of the SCDHI, two typical compound dry-hot events were chosen as case studies according to the Yearbook of Meteorological Disasters in China. One ~~was~~ is a well-known compound drought and heatwave striking Sichuan-Chongqing region with serious consequences during summer of 2006 (Wu et al., 2020), and the other occurred in southern China with adverse impacts on agriculture during July to September of 2009 (Wang et al., 2010). The Sichuan-Chongqing region experienced continuous extreme temperatures during mid-June to late August 2006. The duration and severity of this ~~hot event~~heatwave were the worst on the historical record. Simultaneously, a ~~heavy~~ 100-year drought ~~occurring once in 100 years~~ hit ~~this~~ the region. During this compound event, a population of over ten million was confronted with drinking water shortage, about ~~twenty thousand~~20,000 km^2 of cropland suffered serious losses, and more than one hundred ~~times~~ forest fires broke out. Local governments issued the most serious aridity warning (Zhang et al., 2008). ~~Thus, we take this typical drought-hot event as first case study studies to evaluate the drought/hot monitoring performance of SCDHI.~~ The monthly spatial pattern of this compound event in the Sichuan-Chongqing region is shown in Fig. ~~S7~~S6, indicating that ~~Sichuan-Chongqing~~the region ~~during summer in 2006~~ experienced ~~the~~ moderate to extreme compound dry and hot conditions based on the SCDHI during the 2006 summer. Fig~~.~~ure 8 maps the spatial pattern of this compound event and its impact on vegetation from mid-June to late August at weekly scale. ~~This~~ The event started to appear in the Sichuan-Chongqing region in mid-June 2006, and gradually spread throughout the whole Sichuan-Chongqing region during June 19 to 26. The moderate dry-hot conditions then persisted in the entire Sichuan-Chongqing region from June 27 to August 5 ~~in~~ 2006, lasting for 40 days. ~~The~~ Scattered negative leaf area index ~~was scattered~~appeared in some of the dry-hot affected areas. ~~However, d~~During August 6 to 21, the ~~drought~~dry-hot event became ~~even~~ more severe with the onset of extremely hot temperatures, causing negative vegetation anomalies in most of the affected areas.

The monthly spatial patterns of another compound event in southern China during

July to September of 2009 ~~is~~are shown in Fig. ~~S8~~S7. Overall moderate to heavy compound dry and hot conditions are observed at monthly scale in this region. However, ~~this~~ the event showed large fluctuation at weekly scale. According to the Yearbook, the ~~hot event~~heatwave was divided into two periods: the first stage was from early to late July, and the other stage was from mid-August to early September. The fluctuating compound event caused adverse impacts ~~of~~ on crop pollination and grain filling, resulting in decrease~~ of~~d crop production. Fig~~.~~ure 9 maps the spatial pattern of this event and its impact on the leaf area index at weekly scale. In the first stage, the ~~drought~~dry-hot event hit ~~the~~ most of southern China during July 5 to 12~~, and then~~before it became more severe in the western part of southern China during July 13 to 20. ~~However, t~~The ~~hot event~~heatwave suddenly disappeared ~~from~~ between July 21 to 28, leading to disappearance of the compound event in most of southern China (Fig. 9a). ~~Afterward~~Afterward, the compound event hit this region again from August 6 to 13, and its intensity was particularly strong during August 14 to 21, with ~~severe~~ very hot conditions. Subsequently, the intensity and spatial extent of the compound event faded away in the north of southern China during August 22 to 29. This event extended to most of this region again from August 30 to September 14, with severe dry and hot conditions. The compound events still stayed in this region from September 15 to 22 (Fig. 9b). Despite the short-term event, ~~the anormal change~~reductions in vegetation activity ~~was~~were found in most of the dry-hot affected areas. This complex event indicates that monthly analyses of ~~the~~ compound events ~~-~~can provide an overall situation, but ~~is~~ are un~~not be~~able to capture the serious compound dry and hot conditions caused by ~~a short-term~~ extreme climate ~~anomaly~~ anomalies at shorter time scales. ~~Though such short-term compound dry-hot events only lasted last for days or weeks, such eventsthey can lead to large agricultural losses if they occur within the~~

~~sensitive stages in~~of ~~crop development (i.e.~~e.g.~~, pollination and grain filling) (Mazdiyasni and AghaKouchak, 2015). To provide timely information of the compound dry-hot events, short-time scale analyses and monitoring of such events are essential.~~

Overall, the changes in these two compound dry-hot events based on the SCDHI are consistent with the national weather records (http://www.weather.com.cn/zt/kpzt/) and the Yearbook of Meteorological Disasters in China 2010. In summary, the SCDHI is able to robustly and reliably capture compound dry-hot events at sub-monthly scale, and potentially provide a new tool to objectively and quantitatively analyze and monitor the characteristics of compound dry-hot events in time and space.

3.3 Application of the SCDHI in China

~~Here, w~~We evaluate~~d~~ and compare~~d~~ the spatiotemporal variation of characteristics of compound dry-hot events in China during the growing season (April-September), because such events can more easily cause adverse impact on agriculture and ecosystem during these periods (Hao et al., 2018; Wu et al., 2019; Zscheischler & Fischer, 2020). ~~More precisely, the compound dry-hot events from 1961 to 2018~~ More precisely, the compound dry-hot events and their characteristics (frequency, duration, severity, and intensity) were identified based on 3-month scale SCDHI and run theory ~~at~~with different thresholds (Wu et al., 2018). We further assessed how well climate models are able to represent compound event characteristics.~~, after which the frequency, duration, severity, and intensity of these events were analyzed (A specific case to identify compound dry-hot event is shown in Fig. S9). We then projected their future characteristics changes under the RCP 2.6, 4.5 and 8.5 from 2050 to 2100.~~ Given that short-term concurrent dry and hot events ~~generally~~ often persist for at least weeks (Otkin et al., 2018), only ~~the~~ events that ~~lasting~~ lasted for more than two weeks ~~were~~

are considered ~~in this study~~.

Fig~~.~~ure ~~9~~ 10 shows spatial patterns of key characteristics of the identified compound dry-hot events with the threshold being set to -0.8 in run theory. A high frequency of compound events ~~was~~ is detected in southern China, with occurrence of one event every two years on average.~~,~~ ~~in~~ In contrast, the eastern Tibetan Plateau and northeast China experienced fewer compound events (Fig. 10a), which was generally consistent with ~~the~~ earlier ~~previous~~ studies (Liu et al., 2020; Wang et al., 2016). On average, ~~The~~ compound dry-hot events generally lasted for about ~~twenty~~20 ~~five~~ to ~~thirty-five~~35 days in most of China, while in the eastern Tibetan Plateau, ~~the~~ compound dry-hot event persisted for less than twenty days (Fig. 10b). ~~The~~ Mean severity and intensity of ~~the~~ compound dry-hot event ~~presented relatively~~show somewhat similar patterns in relative terms and ~~showed~~ highlight that most of eastern China experienced the highest severity and intensity (Fig. 10c-d). The spatial patterns are overall similar when using a threshold of -1.3 (Fig. 11) of -1.6 (Fig. S8) in run theory. As expected, frequency and duration tend to decrease, while severity stays similar and intensity tends to increase at more extreme thresholds. White areas indicate regions where no events longer than two weeks occurred.

Overall, southern China ~~suffered~~ suffers more frequent compound dry-hot events, with higher severity and intensity. Southern China is a humid region where evapotranspiration is mainly controlled by energy supply because soil moisture is usually ~~sufficient~~not limiting. ~~For given adequate~~In cases of low soil moisture at the~~in the initiation~~ beginning of a drought, evaporative demand can increase rapidly during a short period ~~when~~ if strong, transient meteorological changes (such as extreme temperature) occur, which in turn ~~exhaust~~ deplete soil moisture ~~to~~ and thus intensify drought conditions (Zhang et al., 2019, Otkin et al., 2018). Moreover, vegetation over southern China is usually abundant and plants tend to suck more water from the soil ~~when high~~during high temperatures, ~~occur,~~ causing evapotranspiration increase and soil moisture decline (Li et al., 2020c; Wang et al., 2016). As a consequence, the~~More surface~~ sensible heat ~~fluxes~~ flux increases, leading to ~~are thus transferred to the near-surface atmosphere to further increase~~ increasing air temperatures (Mo and Lettenmaier, 2015). These land-atmosphere interactions ~~altogether~~ cause the Bowen ratio to increase (Otkin et al., 2013, 2018), creating ~~a~~ favorable conditions for short-term concurrence of droughts and ~~hots~~heatwaves. Therefore, compound dry-hot events with high severity and intensity ~~is~~ are more likely to occur in humid regions~~ with higher severity and intensity~~.

Figure 12 illustrates how well compound event characteristics are captured by climate models. On average, climate models overestimate compound dry-hot frequency in particular for western China, suggesting frequencies that are up to 6 times higher than observations (Fig. 12a). In the east, biases are much small but still show an overestimation. Climate models also generally over~~-~~estimate the duration of and severity of compound dry-hot events, in particular in the west of China, whereas both characteristics are better captured in the east (Fig. 12b, c). Relatively small biases are present for the intensity of compound dry-hot event (Fig. 12d). All in all, the climate models potentially strongly overestimate the occurrence of compound dry-hot events in China, especially for western region, which is likely related to the climate models overestimating the strength of the dependence between SAPEI and STI (Figure S9). ~~Fig. 11 illustrates the spatial patterns of change in frequency, duration, severity, and intensity of the compound dry-hot events under the RCP 2.6, 4.5, and 8.5 scenarios for the years 2050-2100. According to Fig. 11a, the future (2050-2100) cThe compound dry-hot event frequency under all three scenarios is projected to increase in most of east~~

~~China will increase by about one to three times with respect to the reference period (1961-2018). Under the RCP 8.5 scenario, compound dry-hot event at covering about 4% of the study region is are expected to markedly increase by more than five times, which are scatteredmostly in the central to west parts of China. The duration of compound dry-hot event across the east of the study region will mainly show an increase of about 0.5 times, while duration in mid-west China potentially increases by approximately 1.5 times under RCP 8.5 scenarios (Fig. 11b). The spatial pattern of future severity change is similar to the duration; severity in most of east China is projected to increase by about 0.5 time under three scenarios; however, compound dry-hot event severity over mid-west China is expected to more than triple under RCP 8.5 (Fig. 11c). The compound dry-hot event intensity in most of the study region exhibits slight increase for all scenarios in comparison to the historical period. s in most areas under all three scenarioss~~

~~Global warming is very likely to exacerbate the prevalence of the compound dry-hot events (Pfleiderer et al., 2019). The cCumulative density functions of the future variations in compound dry-hot event characteristics considering only temperature and compared to all variables changes were quantified, and the result isare shown in Fig. 12. The frequency and intensity of the future variations in compound dry-hot event do not show large difference between two scenarioscases, while duration and severity display great large increase due towhen only temperature variationchanges are considered, as marked evident by the movement towards the right side of the cumulative density curves.~~

Given the identified biases in climate models in the dependence between SAPEI and STI, multivariate bias adjustment methods are required to reliably estimate future climate risk of compound events in China (Francois et al., 2020). ~~Increasing~~

~~temperature could lead to remarkable increase evapotranspiration, and thus causing more surface sensible heat fluxes into atmosphere (Mo and Lettenmaier, 2015; Zhang et al., 2019). These land-atmosphere interactions altogether cause the Bowen ratio to increase (Otkin et al., 2013, 2018), creating can create a favorable condition for concurrence dries and hots (Otkin et al., 2013, 2018). In short, temperature could be generally the primary factor increasing the compound dry-hot severity and duration (Cook et al., 2014). In addition, trends are often present in individual variables, while can also occur in the dependence between drivers of compound events, which consequently affects associated risks. The~~Furthermore, this dependence may also change under warmer conditions. For instance, the ~~(~~negative~~)~~ correlation between seasonal mean summer temperature and precipitation is projected to intensify in many land regions, which could lead to more frequent dry and hot extremes in addition to long-term trends in temperature and precipitation ~~ing to more frequent extremely dry and hot conditions~~ (Kirono et al., 2017; Zscheischler and Seneviratne, ~~2017a~~2017b)~~,~~ ~~while variation in compound dry-hot event due to the complex interaction between climate variables requires further study (Zscheischler et al., 2020). Effective measures need to be implemented to decrease CO_2 emissions to mitigate compound events~~.~~is need further studied (Zscheischler et al., 2020). Overall, the frequency, severity, duration, and intensity of the compound dry-hot events in China under global warming will increase significantly. Effective measures need to be implemented to decrease the CO_2 emissions for compound event.dry and hot event mitigation.~~

4 Conclusions

~~Under global warming,~~Short-term~~ the~~ compound dry~~ and ~~-hot events ~~tends to be more frequent and short-lived (i.e., days or weeks)~~can cause substantial damage. Correspondingly, a compound drought and heat index should be able to monitor such event at sub-monthly scales in order to timely reflect the evolution of concurrent dry and hot conditions~~ evolution~~. In this study, we developed a multiple time scale (e.g., 3-, 6-, 9, and 12- month) compound drought and heat index, termed as SCDHI, to monitor both short-~~time ~~term (e.g., days or weeks) and long-~~time ~~term (e.g., months) compound events. This index was established based on ~~the ~~a daily drought index (~~i.e., ~~SAPEI) and the Standardized Temperature Index (STI) using a joint probability distribution method. Using the SCDHI, we ~~then quantitively investigated the~~quantified key characteristics (i.e., frequency, intensity, severity, and duration) of ~~the ~~compound dry-hot events in China in the historical period (1961-2018), and ~~revealed ~~investigated how well climate models simulate these characteristics.~~ how they would change in the future (2050-2100) under representative concentration pathway (RCP) 2.6, 4.5, and 8.5 scenarios.~~ The main conclusions of this study are presented as follows: The SCDHI can ~~well ~~monitor simultaneous ~~dries ~~dry and hot~~s~~ conditions ~~detected by SAPEI and STI~~during historic high-impact events. Hereby, the~~The~~ monthly SCDHI can provide an overall situation of the compound dry and hot conditions, ~~but ~~whereas the sub-monthly SCDHI can well capture fluctuation of simultaneous ~~dries ~~droughts and ~~hots ~~heatwaves within a month. SCDHI is further a good indicator of compound dry and hot conditions on vegetation health. ~~It also can ~~also ~~reflect the impact of the compound dry and hot event~~s~~ on vegetation anomalies~~health~~. The SCDHI can offer a new tool to quantitatively measure the characteristics of the compound dry-hot events. It also can provide detailed information such as the initiation, development, decay, and tendency of the compound event for decision-makers and stakeholders to make early and timely warning. ~~In the case ~~study ~~of~~ the~~ China, ~~the southern China~~the south suffered ~~more frequent the~~ compound dry-hot events most frequently, with generally higher severity and intensity. On average, ~~The c~~compound dry-hot events ~~mainly ~~exceeding the light category typically lasted for ~~twenty-~~20~~five~~ to ~~thirty-five~~35 days~~ in China~~. Climate models tend to ~~e~~ overestimate the frequency, duration and severity of compound dry-hot events particularly in the western region of China. In conclusion, the SCDHI offers a new tool to quantitatively measure the characteristics of compound dry-hot events and can provide detailed information on the initiation, development and decay of such events for decision-makers and stakeholders. ~~. will intensify throughout the China in the future. The frequency generally ranged from 0 to 2 times in most of study areas, while the duration and severity biases were about 0 to 1 times. will increase by about one to three times with respect to the reference period. A region with fewer compound event (< 5) would exhibit a multi-fold (more than five times) increase in the future. The duration across east areas mainly increased by 0.5 times, while severity project to increase by about 0.5 to 1 times.~~

Data availability. The observed meteorological datasets are available at http://cdc.nmic.cn/home.do. The CMIP5 datasets are available at https://esgf.llnl.gov.

Author Contributions. Conceived and designed the experiments: JL, SW. Performed the experiments: JL, SW. Analyzed the data: JL. Wrote and edited the paper: JL, SW, ZW, JZ, SG, XC.

Competing interests. The authors declare that they have no conflict of interest.

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Table

Table 1 Categories of compound dry and hot conditions based on SCDHI.

Category	Dry-hot condition	SCDHI
Grade 0	Abnormal	(-0.80, -0.50]
Grade 1	Light	(-1.30, -0.80]
Grade 2	Moderate	(-1.60, -1.30]
Grade 3	Heavy	(-2.0, -1.60]
Grade 4	Extreme	≤ -2

Figure

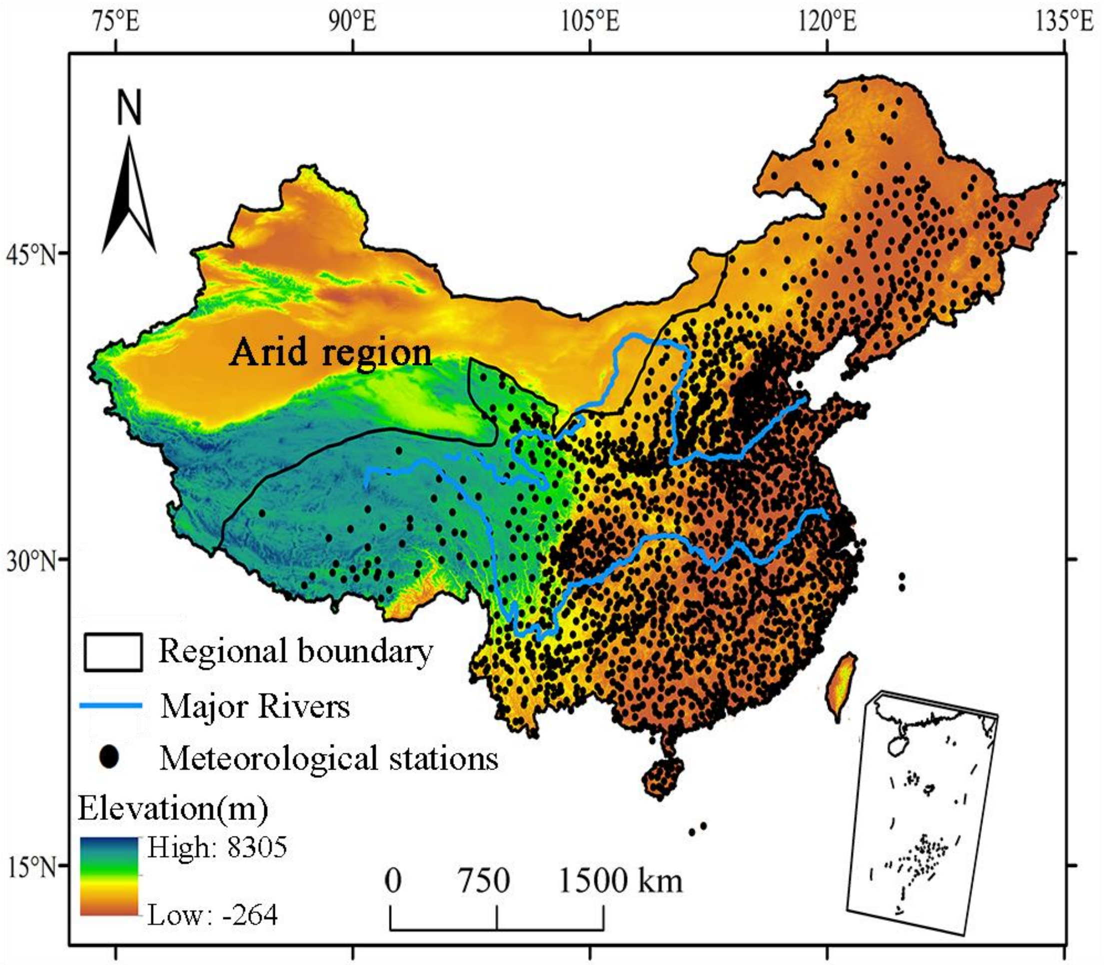


Figure 1 Geographical position of China and local of meteorological stations.

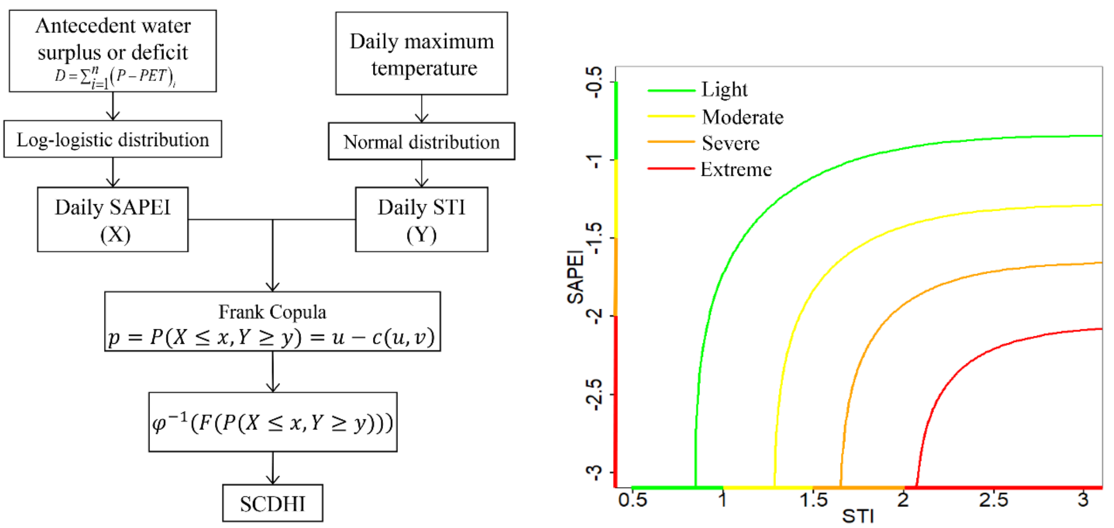


Figure 2 The graphical illustration of the SCDHI construction, and the relation between STI and SAPEI under different severity levels of compound drought and hot conditions (given by the legend). Different colors in abscissa and ordinate represents different drought or hot conditions (i.e., light, moderate, severe, and extreme). The isolines are calculated from a specific calendar day, using the fitted Frank Copula with the parameter being -1.31.

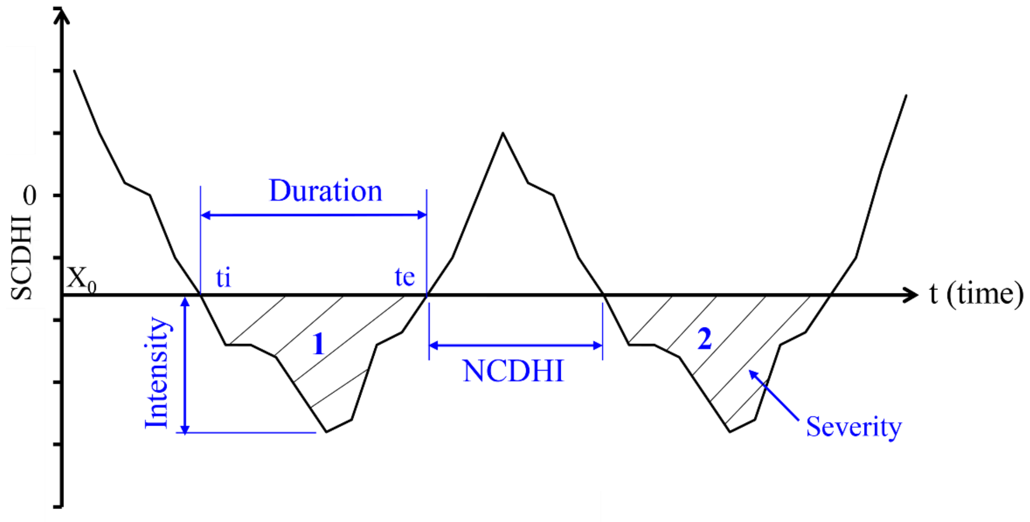
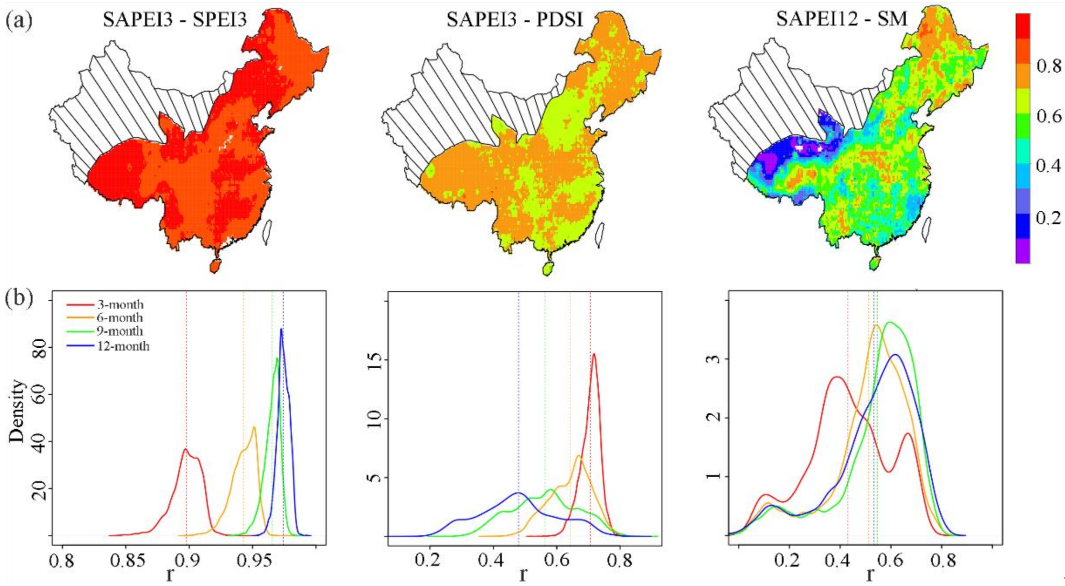


Figure 3 Definition sketch of characteristics of compound dry-hot event showing two events (labeled as 1 and 2), on the basis of run theory. Note: X_0-Truncation level, NCDHC-Non compound dry and hot condition, ti- initiation time, te-termination time.



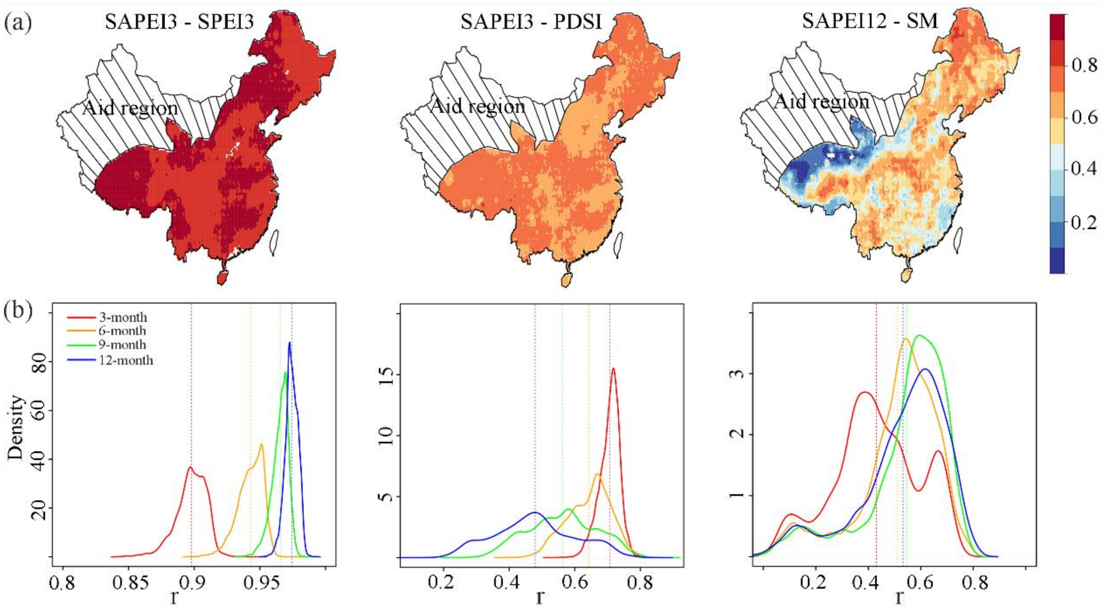


Figure ~~2~~ 4 (a) The spatial pattern of the correlations between monthly SAPEI and SPEI/PDSI, and between daily SAPEI and soil moisture (SM), and (b) The density plot for the correlation coefficients between SAPEI and SPEI/PDSI/SM. The monthly SAPEI is computed by averaging the daily values in each month.

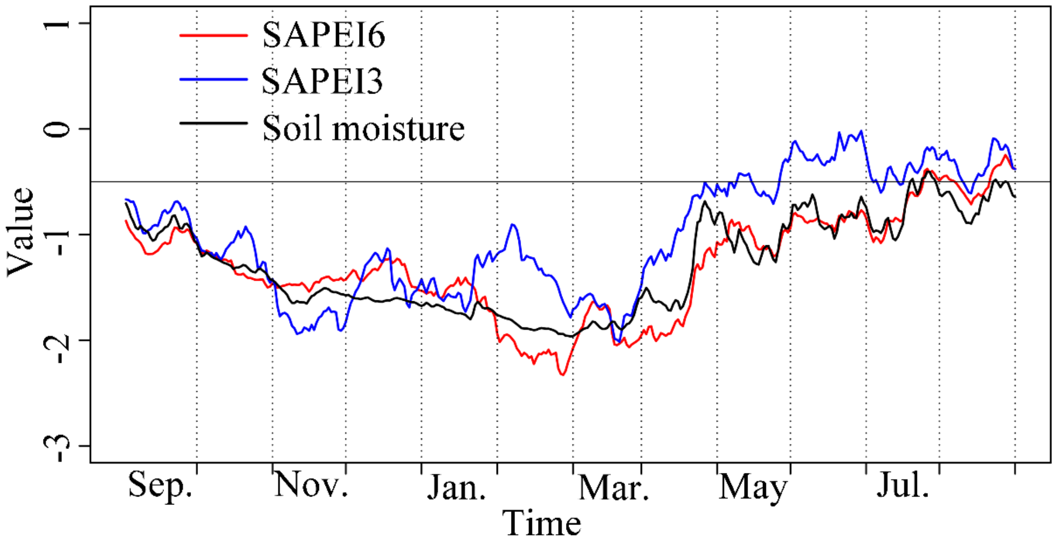
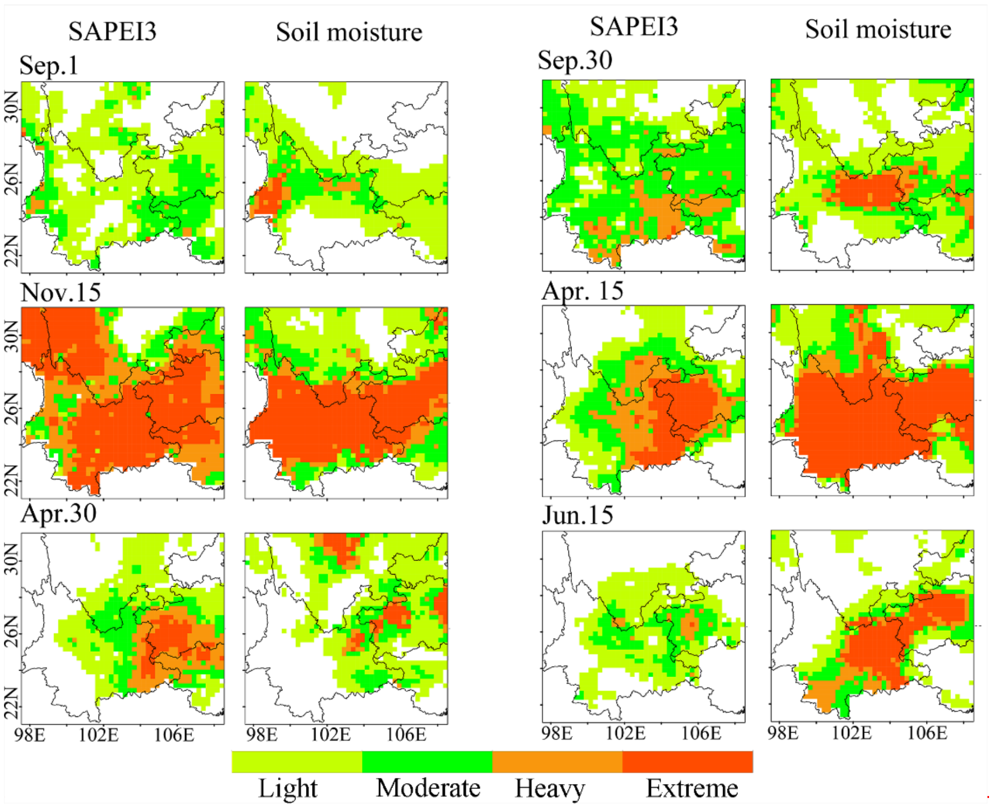


Figure ~~3~~ 5 SAPEI and soil moisture series during the 2009/2010 drought event over the southwest China. Shown are ~~The series were~~the spatially averaged ~~merged~~ series. The value of solid black line is at -0.5, indicating the distinction between drought and non-drought conditions.



~~Figure 4 Daily evolutions of the 2009/2010 drought event over the southwest China monitored by 3-month SAPEI and soil moisture.~~

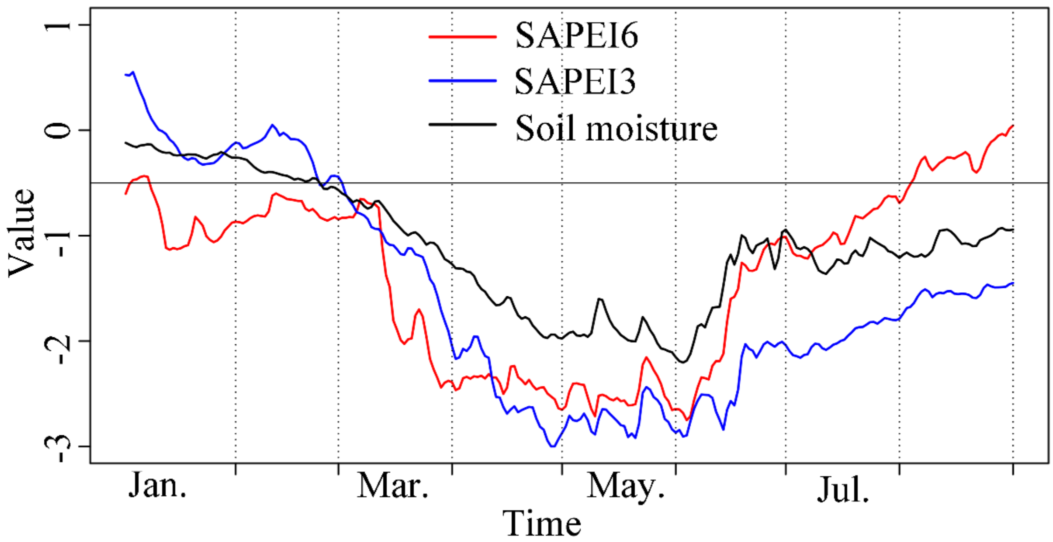
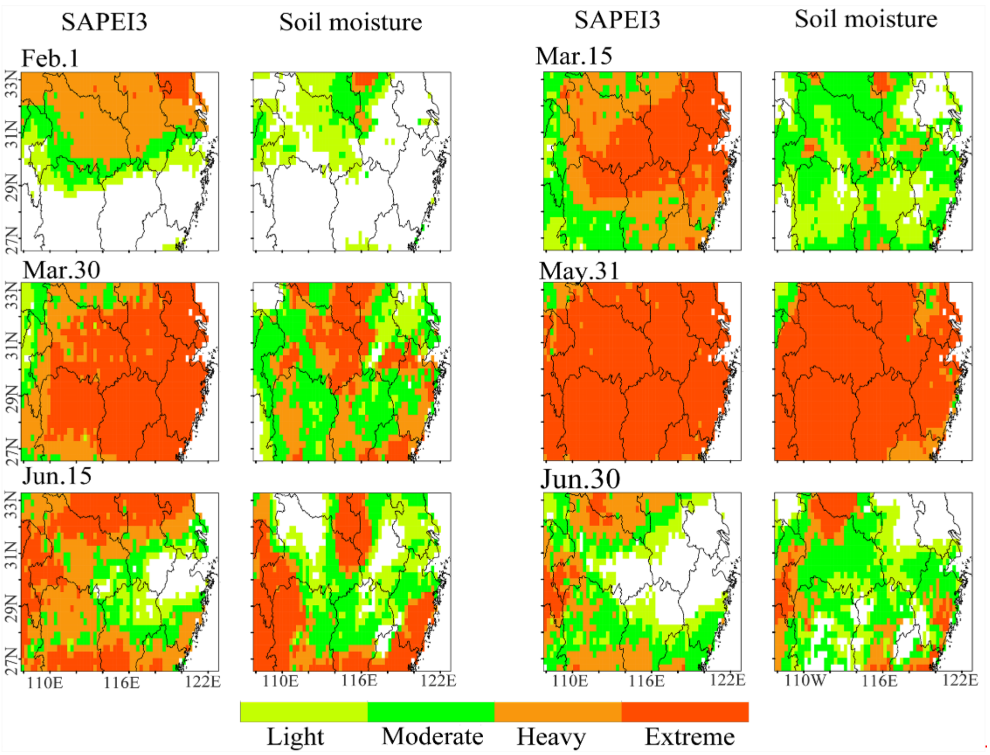
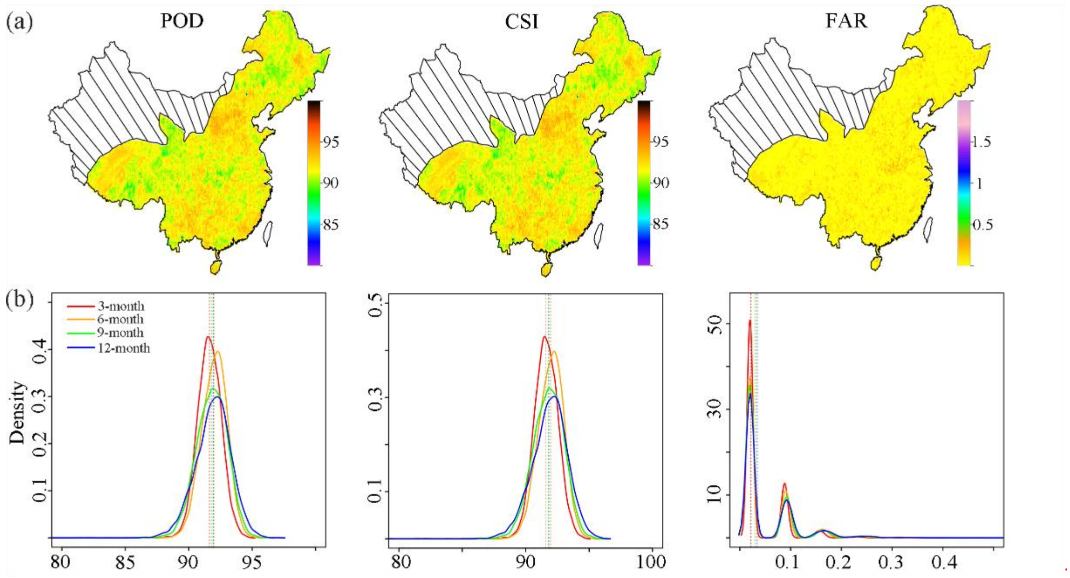


Figure ~~5~~ 6 SAPEI (3- and 6-month) and soil moisture series during the 2011 drought event over the middle and lower reaches of the Yangtze River. Shown are t~~T~~he ~~series were~~ spatially averaged ~~merged~~ series. The value of solid black line is at -0.5, indicating the distinction between drought and non-drought conditions.



~~Figure 6 Daily evolutions of the 2011 drought event over the middle and lower reaches of the Yangtze River monitored by 3-month SAPEI and soil moisture.~~



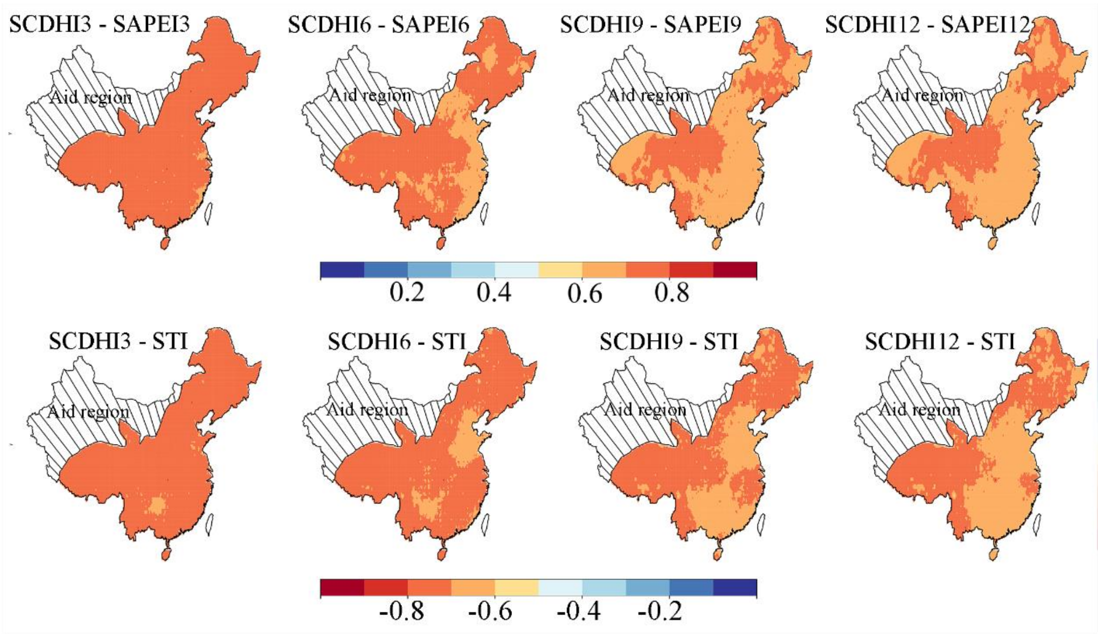
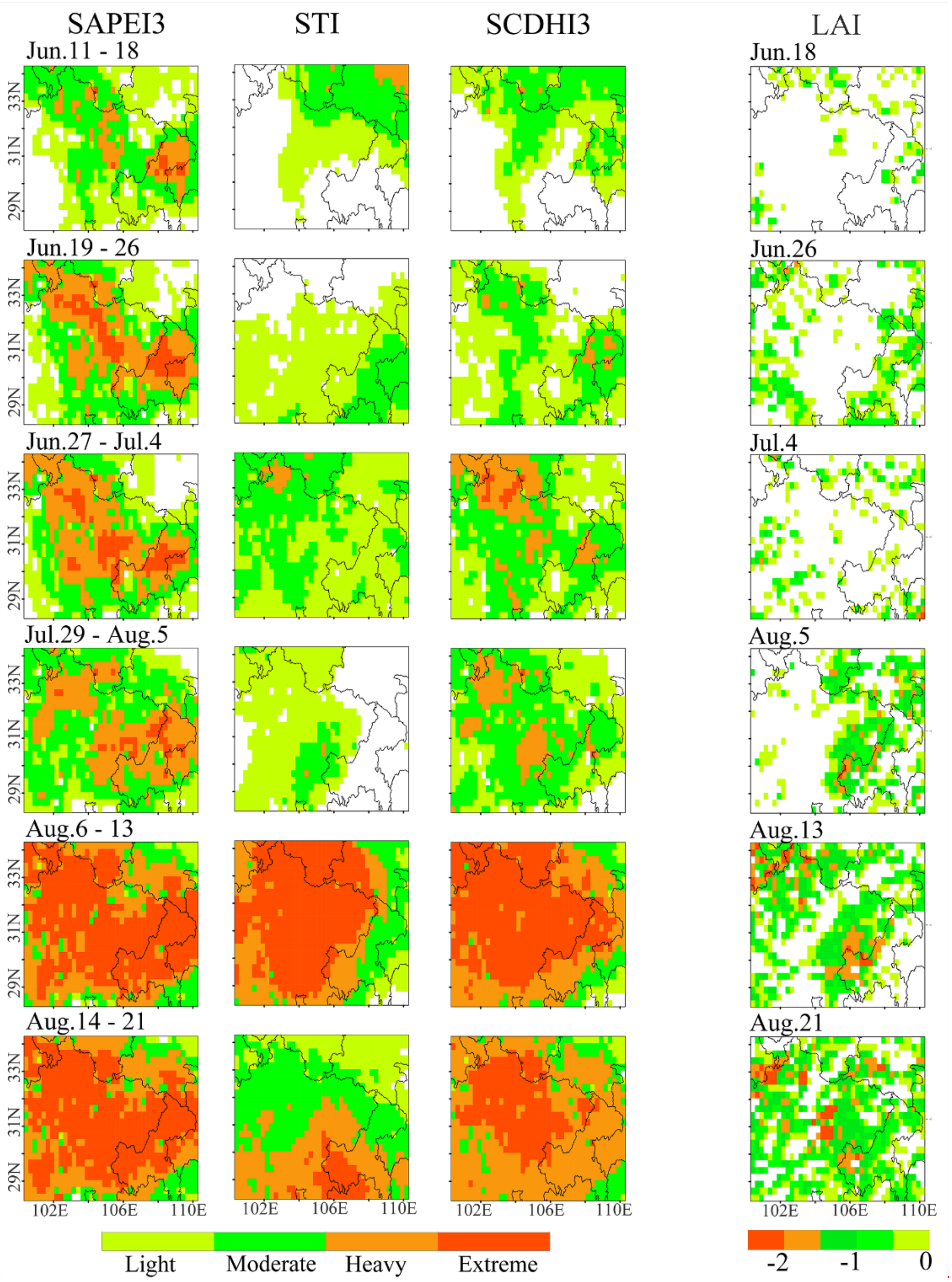


Figure ~~7~~ 7 The correlation between SAPEI/STI and SCDHI during the historical period (1961-2018).~~(a) The spatial pattern of probability of detection (POD, %), critical success index (CSI, %), and false alarm ratio (FAR, %) for 3-month SCDHI from 1961 to 2018, and (b) Density plot for POD, FAR, and CSI for 3-, 6-, 9-, 12-month SCDHI from 1961 to 2018~~.


SAPEI3
STI
SCDHI3
LAI
Jun.11 - 18
Jun.18
Jun.19 - 26
Jun.26
Jun.27 - Jul.4
Jul.4
Jul.29 - Aug.5
Aug.5
Aug.6 - 13
Aug.13
Aug.14 - 21
Aug.21
33N
31N
29N
102E
106E
110E
Light
Moderate
Heavy
Extreme
-2
-1
0

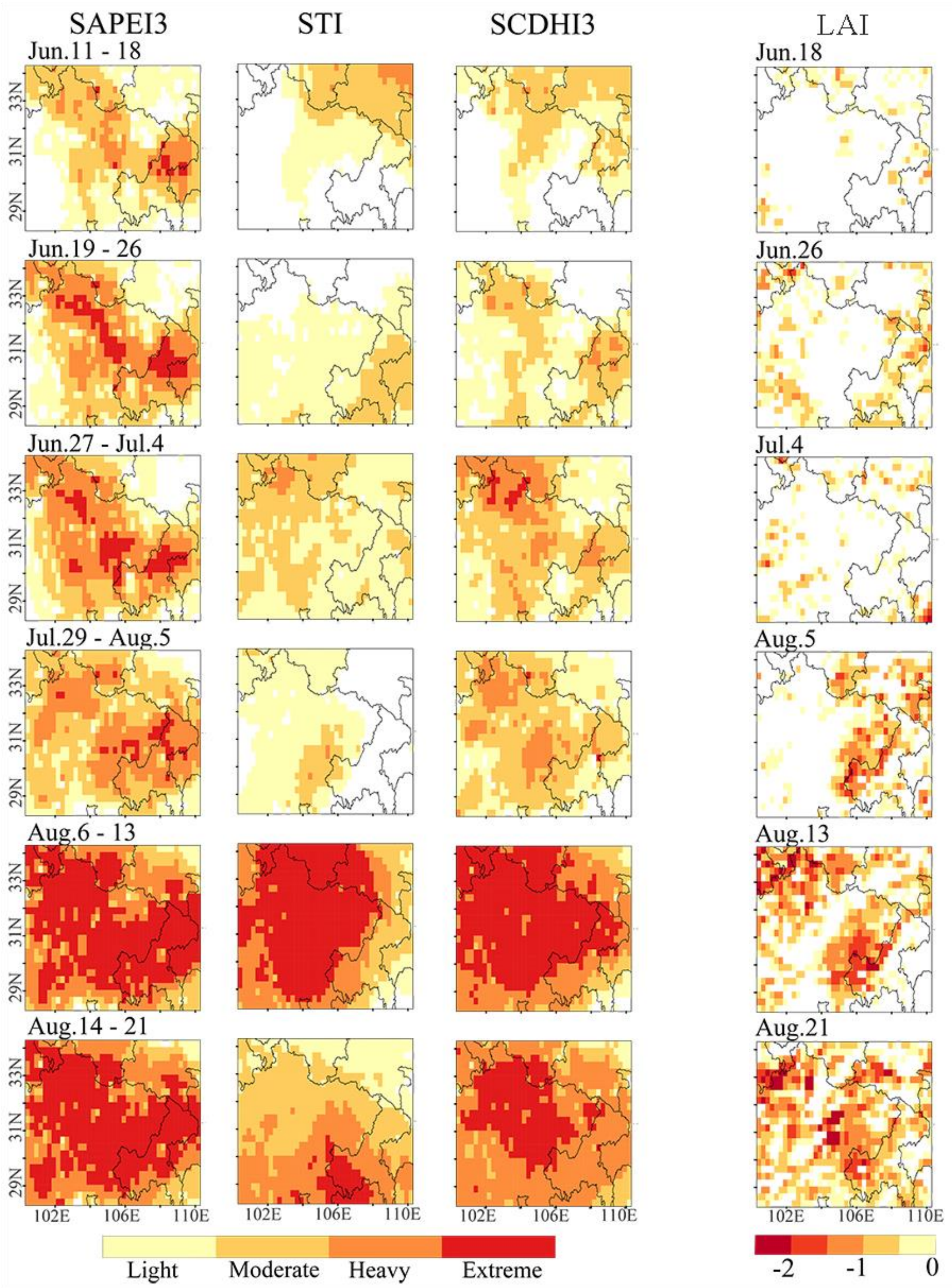
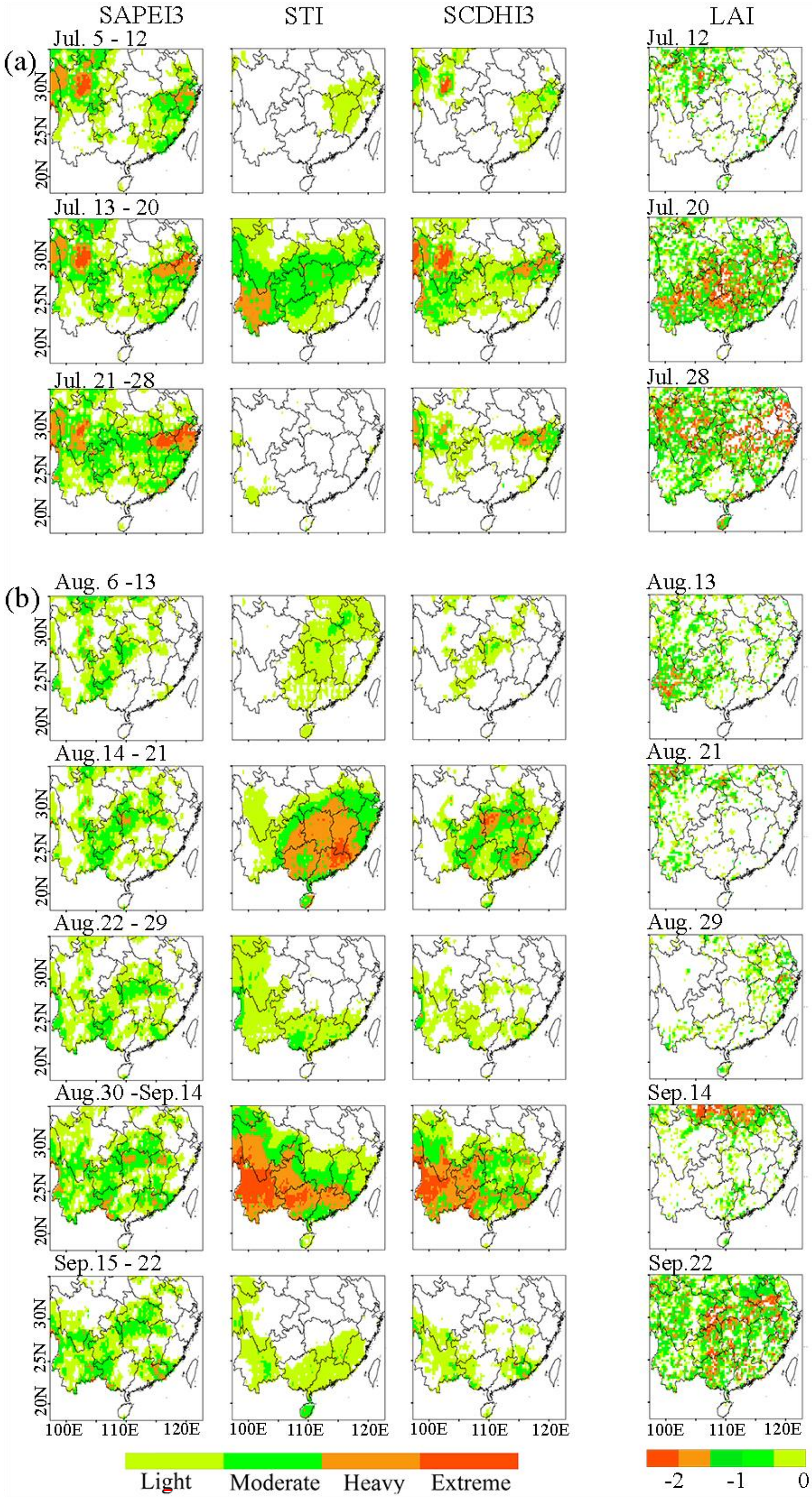


Figure 8 The spatial evolutions of the compound dry and hot event over the Sichuan-Chongqing region in 2006 and its impact on vegetation as weekly averages.



SAPEI3
STI
SCDHI3
LAI
(a)
Jul. 5 - 12
Jul. 12
Jul. 13 - 20
Jul. 20
Jul. 21 -28
Jul. 28
(b)
Aug. 6 -13
Aug.13
Aug.14 - 21
Aug. 21
Aug.22 - 29
Aug. 29
Aug.30 -Sep.14
Sep.14
Sep.15 - 22
Sep.22
30N
25N
20N
100E
110E
120E
Light
Moderate
Heavy
Extreme
-2
-1
0

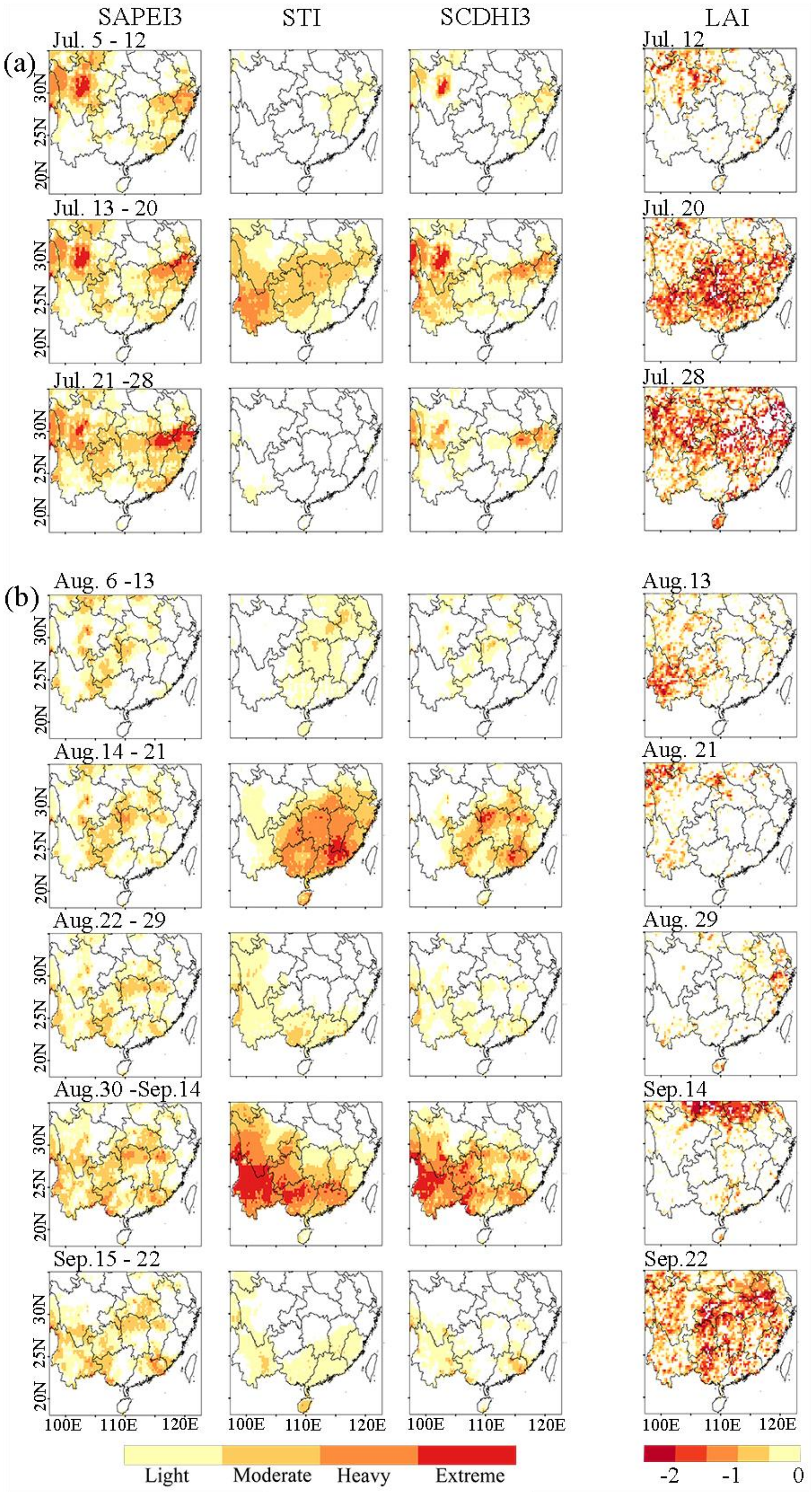
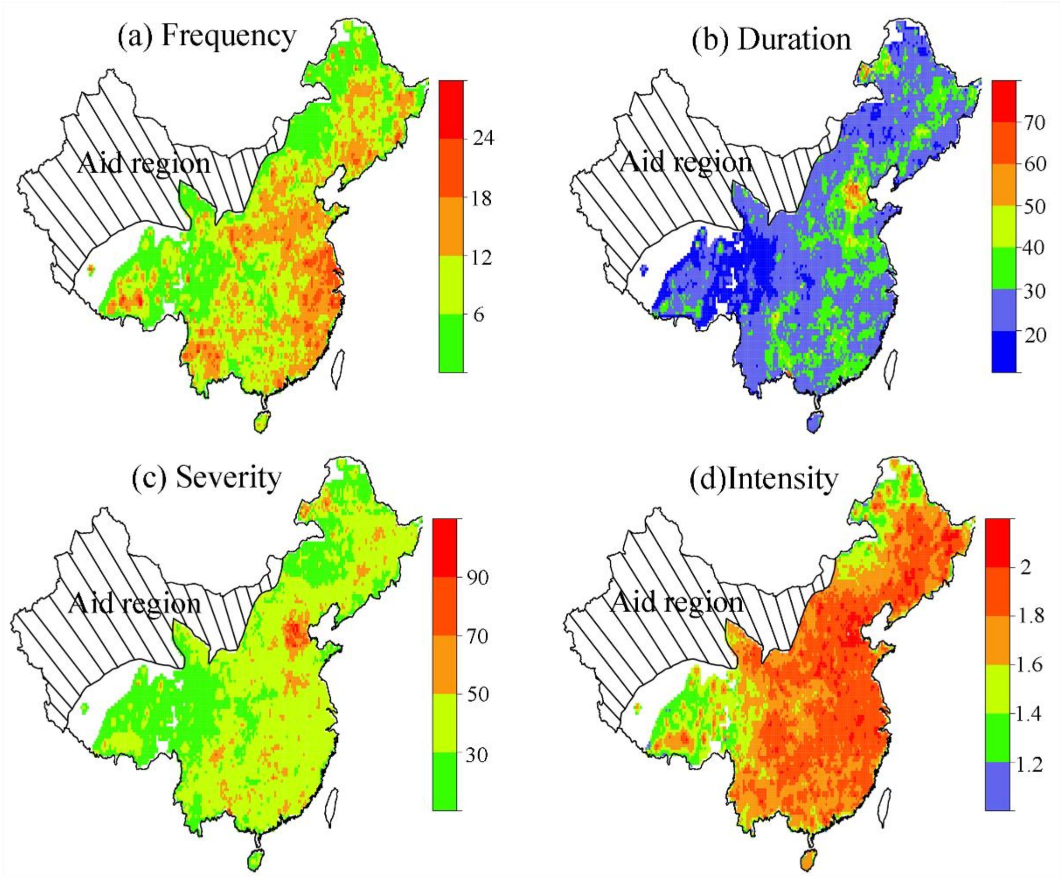


Figure 9 The spatial evolutions of the compound dry and hot event over the southern China in 2009 and its impact on vegetation as weekly averages.


(a) Frequency
Aid region
24
18
12
6
(b) Duration
Aid region
70
60
50
40
30
20
(c) Severity
Aid region
90
70
50
30
(d)Intensity
Aid region
2
1.8
1.6
1.4
1.2

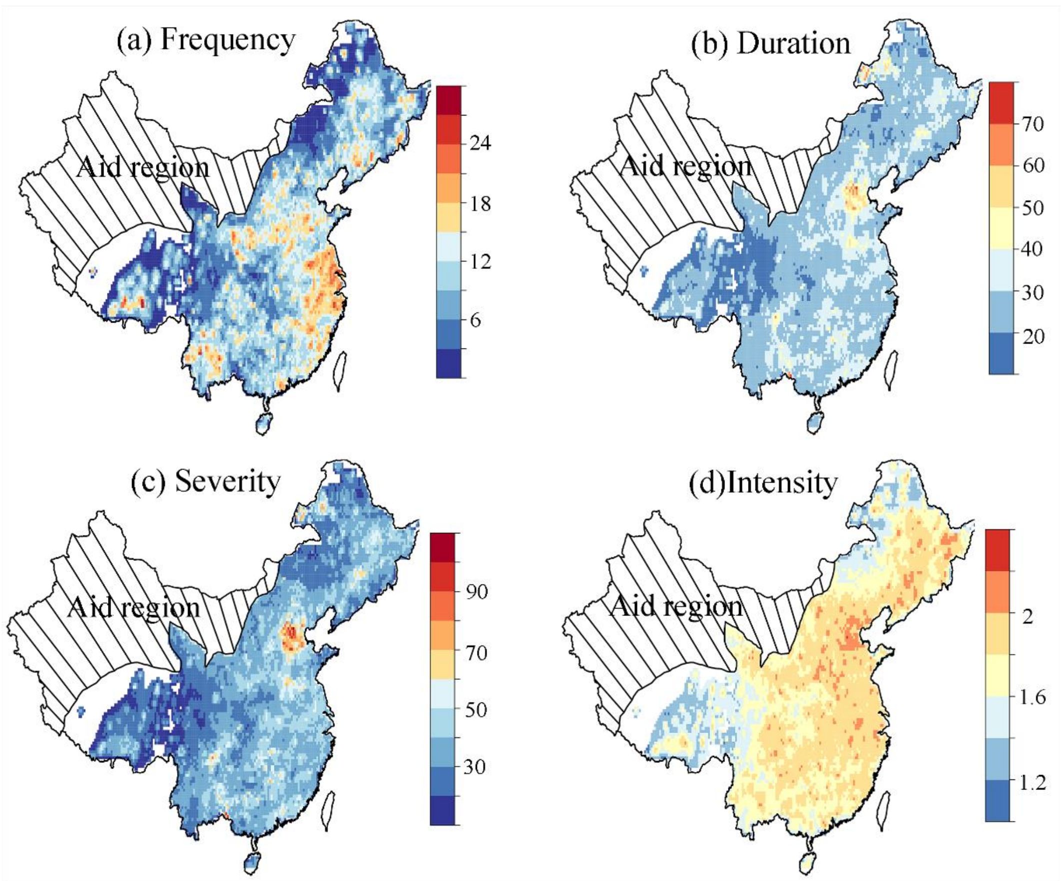

(a) Frequency
Aid region
24
18
12
6
(b) Duration
Aid region
70
60
50
40
30
20
(c) Severity
Aid region
90
70
50
30
(d)Intensity
Aid region
2
1.6
1.2

Figure 10 The spatial pattern of the key characteristics of ~~the~~ compound dry and hot events in China from 1961 to 2018, using the threshold of -0.8 in run theory. Frequency (a) refers to the total events during historical period; duration (b), severity (c), and intensity (d) are the average values of all events. White color indicates there are no events. Only events longer than two weeks are considered.

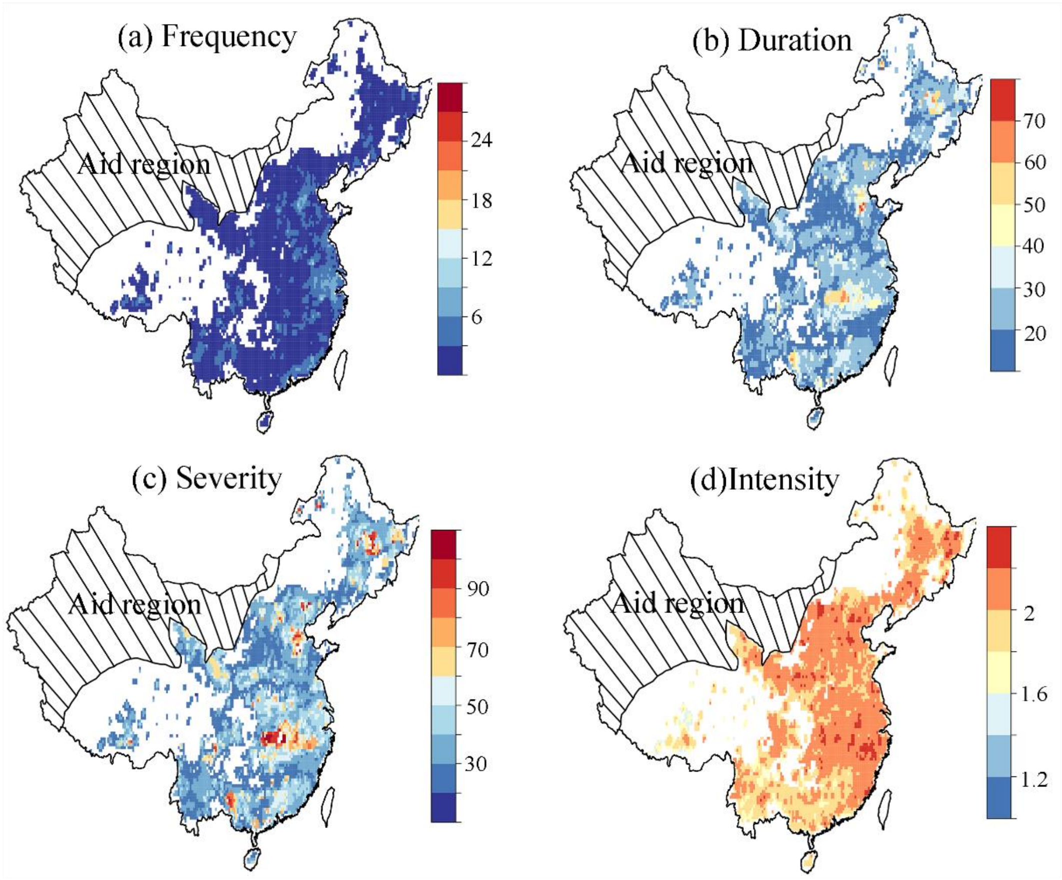
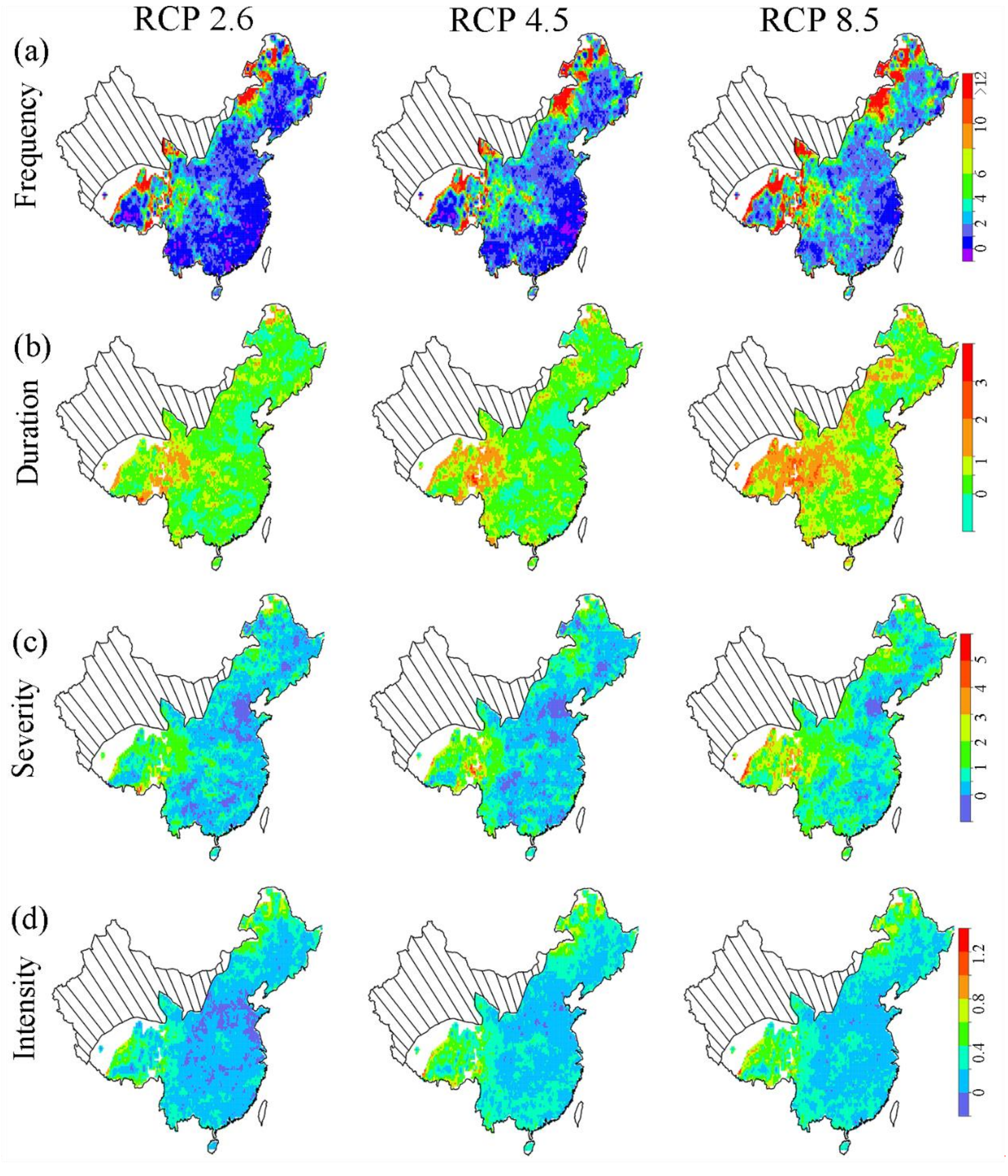


Figure 11 The same as Figure 10, but using the threshold of -1.3 in run theory. The definition of the frequency, duration, severity, and intensity are the same as Figure 10. White color indicates there are no events.


RCP 2.6
RCP 4.5
RCP 8.5
(a)
Frequency
(b)
Duration
(c)
Severity
(d)
Intensity
0 2 4 6 10 >12
0 1 2 3
0 1 2 3 4 5
0 0.4 0.8 1.2

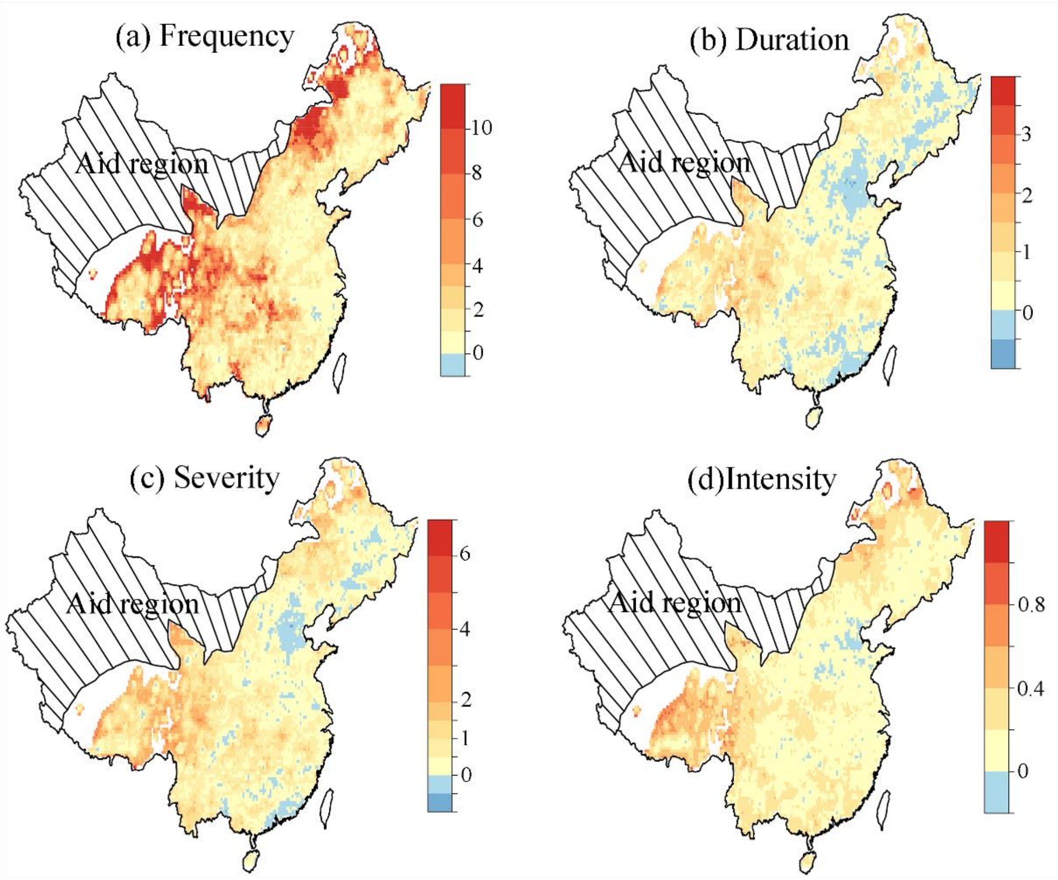
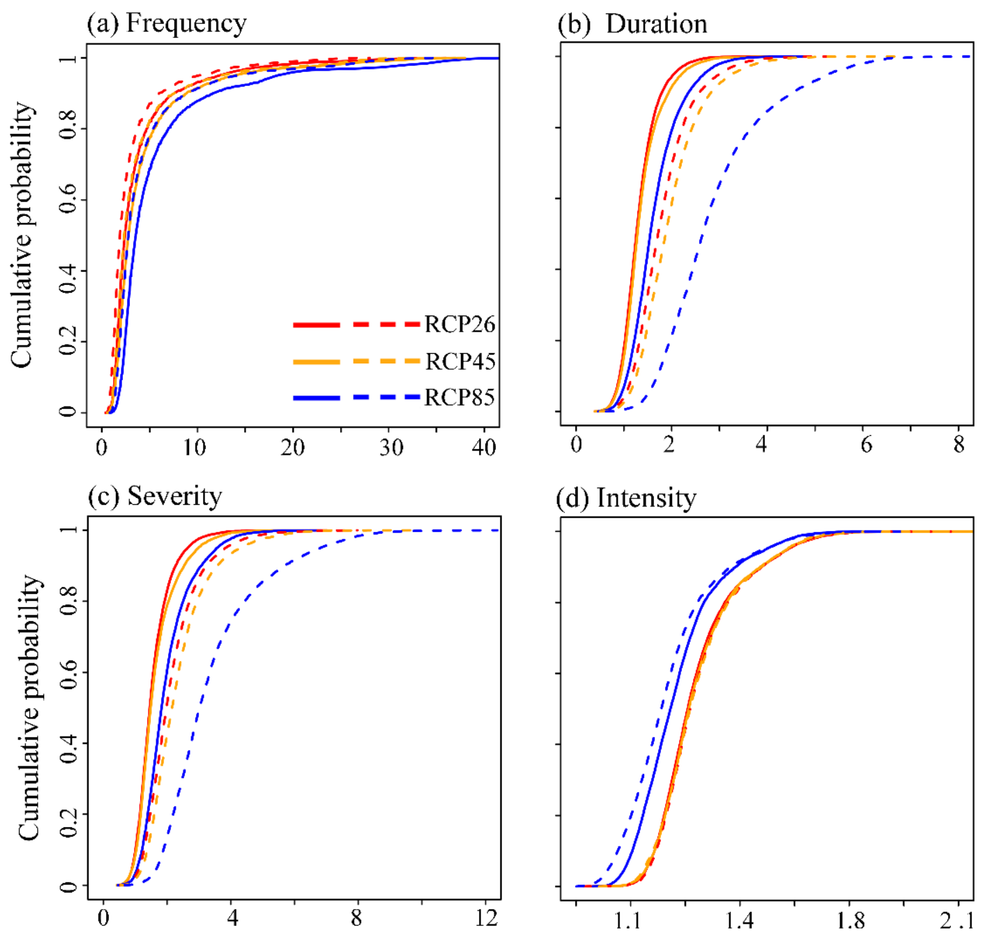


Figure 12 Relative climate model biases in the characteristics of the compound dry and hot events in China. The biases are computed as the ratio of the difference between model and observational values to the observational values. The definition of the frequency, duration, severity, and intensity are the same as Figure 10. White color indicates there are no events. The periods were from 1961-2005. The threshold in run theory is -0.8. ~~Figure 11 Future changes in characteristics of the compound dry and hot events under the RCP 2.6, RCP4.5 and RCP8.5 scenarios. The change values were the ratio of the future value to the reference values. Reference period: 1961-2018, and future period: 2050-2100.~~



~~Figure 12 Cumulative probability of future changes (multiple) in of the compound dry-hot event characteristics. The dash lines indicate future characteristics changes only considered temperature change, while solid lines represent the future changes driven by all variable variation.~~