Probabilistic impacts of compound dry and hot events on global gross primary production

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Abstract
As the basis of food and fiber production, gross primary production (GPP) plays a critical role in the growth of vegetation. Understanding the response of GPP to climate extremes is important for ensuring food security under ongoing global warming. Plenty of evidence shows that the recent widespread dry or hot events across the globe have significant influences on GPP, yet little is known about their joint impacts. Here, we reveal a high risk of compound dry and hot events globally, in response to the strong negative dependence of precipitation and temperature, which leads to a substantial negative impact on GPP for both crop and pasture ecosystems. Using a meta-Gaussian model, we show that the probability of a reduction in global terrestrial GPP increases significantly under compound dry and hot conditions relative to their individual counterparts. Further, the risk of GPP reductions increases with the intensified severity of compound dry and hot events across the globe. These results unravel the sensitivity of GPP to compound dry and hot conditions and highlight the need to account for the influence of compound events when assessing the carbon budget.

1. Introduction
As the largest carbon flux, gross primary production (GPP) plays an important role in the global ecosystem carbon balance (Xu et al 2019, Wang et al 2021a). Climate extremes, such as droughts and hot events, have a strong influence on the terrestrial ecosystem globally, mainly through their impacts on GPP (Ciais et al 2005, Peng et al 2013, Zscheischler et al 2014b, Chen et al 2019, Stocker et al 2019). The changing climate has altered and is projected to further increase the odds of weather and climate extremes and, consequently, may exert an unprecedented impact on terrestrial ecosystems. In view of the feedback between climate and carbon budgets, a better understanding of the impact of extreme climates on GPP is of crucial importance to enable one to devise adaptation and mitigation strategies under global warming.

Many investigations have reported the negative impact of extreme climates on GPP (Wang et al 2018, Xu et al 2019). Thereinto, extremely high temperatures and droughts are referred to as two main factors which can reduce GPP via their influence on photosynthesis and water availability (Zhao and Running 2010, Von Buttlar et al 2018). For instance, Yuan et al (2016) found that the severe heatwave and drought during the summer of 2013 in southern China caused a large reduction in GPP and crop yield loss by 90.91 kg ha$^{-1}$ on average. Based on zonal analysis, Yu et al (2017) concluded that the drought during 2000–2011 caused 48% reduction in GPP in the mid-latitudes at 30°N–50°N. Chen et al (2019) revealed that GPP in northern China is vulnerable to droughts, while that in southern China is vulnerable to temperature extremes. In general, the widely negative responses of GPP to dry and hot related events may exert profound impacts on carbon cycle variability and lead to a carbon sink anomaly at both regional and global scales.

As a consequence of climate change, the likelihood of precipitation and temperature events has substantially altered globally. In particular, the changing dependence between multiple climate drivers or variables modifies the risk of compound events,
and has made some unprecedented compound events emerge in recent decades, such as the compound dry and hot events during 2003 in Europe (EU), 2006 in southwestern China, 2010 in Russia, 2013 in Australia (AUS), 2014 in California, and 2016 in northeastern China (Barriopedro et al. 2011, AghaKouchak et al. 2014, Sedlmeier et al. 2017, Li et al. 2018, Mukherjee and Mishra 2021). Despite a debate on the variability of droughts across the globe (Dai 2012, Sheffield et al. 2012), a consensus has been broadly reached that compound dry and hot events have increased globally under global warming (Zscheischler and Seneviratne 2017, Hao et al. 2018), which usually leads to profound socio-economic and ecological consequences. A noteworthy issue is that further risk can be caused by compound dry and hot events to terrestrial GPP, as there is an interaction between droughts and hot events (von Buttler et al. 2018). Ciais et al. (2005) showed that GPP experienced an unprecedented reduction of 30% over EU during 2003 due to the extreme heat and drought, which reversed the ecosystem carbon sequestration for four years. Based on simulations from the Coupled Model Intercomparison Project Phase 5, Zscheischler et al. (2014b) found that compound dry and hot conditions play a dominant role in driving the negative extremes in global GPP. Similarly, a higher likelihood of vegetation reduction caused by compound dry and hot events has been found in arid and semi-arid regions than with individual drought or hot events (Hao et al. 2021). Although several studies have suggested that droughts in conjunction with hot events may cause a strong reduction in terrestrial GPP (Zscheischler et al. 2014b, von Buttler et al. 2018, Chen et al. 2019, Zhu et al. 2021), how much these GPP reductions might be under different severity levels of compound dry and hot conditions is still poorly studied, especially from a probabilistic perspective. Note that traditional assessments based on univariate analysis may underestimate the likelihood of compound events (Zscheischler and Seneviratne 2017, Zscheischler et al. 2018), leading to an understimation of the impact accordingly. Furthermore, besides the observed increased frequency, severity, and duration, as well as the spatial extent in recent decades, compound dry and hot events are projected to further increase across most regions of the globe in the 21st century (Feng et al. 2020, Wu et al. 2021), which may cause more stress on the ecosystem. Thus, investigation of the effect of compound events on GPP is important to better understand the terrestrial carbon cycle under global warming.

In this study, we mainly focus on the impact of compound dry and hot events on GPP from a probability perspective at both global and regional scales. As crops and pasture are vulnerable to the variability of droughts and hot events (Reichstein et al. 2013, Lesk et al. 2016), we further specifically focus on these two types of ecosystems. Besides addressing the comparison between individual and joint effects of dry and hot events on GPP, we also assess the risk of impacts and GPP anomalies induced by different severity levels of compound conditions. The outline of this study is as follows. Section 2 describes the data and methods. Section 3 presents the impact of compound dry and hot events on GPP. Section 4 presents a brief discussion, and section 5 gives the main conclusions.

2. Data and methods

2.1. Data

The observation-based datasets of monthly precipitation, temperature, and potential evapotranspiration with 0.5° horizontal resolution are taken from the Climate Research Unit (CRU TS v4.04, 1982–2018) of the University of East Anglia (Harris et al. 2020). Two global GPP datasets with a relatively long time series covering 1982–2018 are applied for analysis. The first dataset based on the satellite-based near-infrared reflectance of vegetation (NIRv) with 0.05° horizontal resolution at the monthly scale is obtained from the National Tibetan Plateau Data Center (Wang and Zhang 2020, Wang et al. 2021b). The second, with 0.05° horizontal resolution and an eight-day interval, generated using the revised eddy covariance light-use-efficiency (LUE) model, is available online at https://doi.org/10.6084/m9.figshare.8942336.v3 (Zheng et al. 2020). For consistency, the GPP data are bilinearly interpolated to the same resolution as the climate data (i.e. 0.5°). Prior to all the calculations, the linear trend of temperature, precipitation, and GPP has been detrended to remove the effect of climate change signals or other factors on the long-term trend (Zscheischler and Seneviratne 2017, Liu et al. 2018). Notably, we only investigate the region where both the GPP datasets have data in this study. As extremes that occur in warm seasons usually have severe impacts on GPP (Chen et al. 2019), here we only focus on that time, denoted as the three months with the highest temperature during 1982–2018 (as shown in figure S1 available online at stacks.iop.org/ERL/17/034049/mmedia in the supplementary material), and all the analyses are based on the seasonal mean. Additionally, the global cropland and pastureland data from 2000 are available from the NASA Socioeconomic Data and Applications Center (SEDAC) (Ramankutty et al. 2010a, 2010b), which are used as the region of crop and pasture in this study (as shown in figure S2). By employing this crop or pasture land area fraction as the weights, the time series of precipitation, temperature, and GPP data at the global scale are obtained by taking the average of the gridded data.

In addition, considering that climate conditions differ with regions, we further divide the global land area into eight subregions (Yao et al. 2020), including North America (NAM), South America (SAM), EU,
2.2. Identification of compound dry and hot events

The compound dry and hot events are defined as the seasonal precipitation $P$ below or equal to a certain threshold in conjunction with the accompanying seasonal temperature $T$ above a certain threshold. We use the copula model to describe the joint distribution function of $P$ (denoted as $X$) and $T$ (denoted as $Y$) to derive the compound event, which is expressed as:

$$p = P(X \leq x, Y > y) = P(X \leq x) - P(X \leq x, Y \leq y) = u - C(u, v)$$

where $p$ is the joint probability of compound dry and hot events; $u = P(X \leq x)$ and $v = P(Y \leq y)$ are the marginal probability of the random variables $X$ and $Y$, respectively, which are calculated based on the commonly used Gringorten plotting position (Gringorten 1963), a method that can avoid the parametric assumption of distribution, as shown in equation (2); $C$ is the copula model. It is worth mentioning that a variety of copula families have been employed to characterize the joint distribution of multivariate random variables, such as Archimedean copulas, the empirical copula, and the elliptical copula (Nelsen 2006; Hao and Singh 2016). These copulas are used to construct various dependence structures. For instance, the $t$ copula can model the symmetric dependence, while the Clayton copula allows the lower-tail dependence, which is asymmetric. As a Gaussian copula can be used to construct both negative and positive dependences of multiple variables (Trivedi and Zimmer 2005), it has been commonly used in hydrology and meteorology, including the analysis of compound dry and hot events. Following some existing investigations (e.g. Hao et al 2017), here we use a Gaussian copula to model the joint probability to characterize compound dry and hot conditions.

The nonparametric method of the Gringorten plotting position can be expressed as:

$$p(z_i) = \frac{n_i - 0.44}{n + 0.12}$$

where $p(z_i)$ is the probability of $z \leq z_i$ (i.e. precipitation or temperature) for the period $i$; $n_i$ is the number of occurrences of $z \leq z_i$; $n$ is the length of the data.

We also employ a combination of the Standardized Precipitation Index (SPI) (McKee et al 1993) and the Standardized Temperature Index (STI) (Zscheischler et al 2014a) to denote the compound dry and hot event using both a statistical model (see method below) and an empirical counting approach. Correspondingly, compound dry and hot events are defined as concurrent exceedances of the SPI below or equal to a certain threshold SPI0 and the STI above a certain threshold STI0. The 1 month timescale of the SPI and STI is calculated from the seasonal mean of precipitation and temperature during the warm season. Following the drought categories classified by the U.S. Drought Monitor (Svoboda et al 2002), we choose three thresholds of SPI, namely, $-0.5$, $-0.8$, and $-1.3$, to define abnormal, moderate, and severe dry conditions. Correspondingly, three thresholds of STI at 0.5, 0.8, and 1.3 are used to define abnormal, moderate, and severe hot events, respectively. Thus, three categories of compound conditions from the least to most severe levels, namely, abnormal, moderate, and severe compound dry and hot events, are defined as $\text{SPI} \leq -0.5$ & $\text{STI} > 0.5$, $\text{SPI} \leq -0.8$ & $\text{STI} > 0.8$, and $\text{SPI} \leq -1.3$ & $\text{STI} > 1.3$, respectively.

In addition, we choose three cases of $\text{SPI} = -0.5$ & $\text{STI} = 0.5$, $\text{SPI} = -0.8$ & $\text{STI} = 0.8$, and $\text{SPI} = -1.3$ & $\text{STI} = 1.3$, as the proxies of different severity levels of compound in the subsequent analysis. As the empirical counting approach usually requires large samples (Zscheischler and Seneviratne 2017), we also choose 0 as the threshold of SPI/STI to obtain enough compound events to render the results relatively robust.

2.3. Conditional probability

By referring to the method used to approach the crop yield in Feng et al (2019), we transform GPP into a standardized form, namely, the Standardized Gross primary production Index (SGI). Therefore, the impact of compound dry and hot events on GPP can be assessed using the conditional distribution of SGI under different compound dry and hot conditions (denoted by SPI and STI) based on a meta-Gaussian model (Feng et al 2019, Leng and Hall 2019). The trivariate conditional distribution of $Z$ (i.e. SGI) given $X$ (i.e. SPI) and $Y$ (i.e. STI) can be expressed as (Wilks 2011, Hao et al 2016, Feng et al 2019):

$$Z|X, Y \sim \mathcal{N}(\mu_{Z|X,Y}, \Sigma_{Z|X,Y})$$

where $\mu_{Z|X,Y}$ is the conditional mean, and $\Sigma_{Z|X,Y}$ is the covariance matrix.

Further, we denote $\Sigma$ as the covariance matrix of $[X, Y, Z]$, which is expressed as:

$$\Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} & \Sigma_{13} \\ \Sigma_{21} & \Sigma_{22} & \Sigma_{23} \\ \Sigma_{31} & \Sigma_{32} & \Sigma_{33} \end{pmatrix}$$

where $\Sigma_{11}$ is the covariance matrix of $[X, Y]$; $\Sigma_{22}$ is the covariance matrix of $Z$; $\Sigma_{12}$ and $\Sigma_{21}$ are the covariance matrix of $[X, Y]$ and $Z$.

Correspondingly, the $\mu_{Z|X,Y}$ and $\Sigma_{Z|X,Y}$ in equation (3) can be expressed as (Wilks 2011, Hao et al 2016, Feng et al 2019):

$$\mu_{Z|X,Y} = \mu_z + \Sigma_{21}^{-1} \Sigma_{11}^{-1} (x - \mu_x)$$

$$\Sigma_{Z|X,Y} = \Sigma_{22} - \Sigma_{21} \Sigma_{11}^{-1} \Sigma_{12}$$
where $\mu_1$ is the mean of the variable $Z$, and $\mu_{xy}$ is the mean of the vector $[X, Y]$.

Additionally, to evaluate the impact of individual dry or hot events on GPP, bivariate conditional distribution is also employed, which performs a similar calculation to the trivariate case (not shown here).

### 2.4. Classification of climatic zones

The response of vegetation to climate extremes may differ with climatic zones. Following existing studies (Zhang et al. 2020), we employ the commonly used aridity index $(AI)$ to divide the wetness/dryness zones, which can be expressed as (UNEP 1997):

$$AI = \frac{P_{ma}}{ET_{ma}}$$

where $P_{ma}$ is the mean annual precipitation, and $ET_{ma}$ is the mean annual potential evapotranspiration.

Accordingly, the global land can be classified into five subtypes: hyper-arid ($AI < 0.03$), arid $(0.03 \leq AI < 0.2)$, semi-arid $(0.2 \leq AI < 0.5)$, sub-humid $(0.5 \leq AI < 0.65)$, and humid $(AI \geq 0.65)$, as shown in figure S3. Uncertainties exist in impact assessment over hyper-arid regions because of the lack of available GPP data in large parts of that area. Thus, we only focus on the four subtypes of climatic zones, excluding hyper-arid regions in the subsequent analysis.

### 3. Results

#### 3.1. The probability of compound dry and hot events

The probability of compound dry and hot events as well as the Pearson correlation coefficients between precipitation and temperature during the warm season are shown in figure 1. It is seen that high probability occurs mainly over western America, western Eurasia, southern AF, southern and northeastern China, and AUS during 1982–2018 (figure 1(a)). Correspondingly, a negative correlation between precipitation and temperature is observed across most of the globe (accounting for 86% of the global land area), indicating that low precipitation tends to be coupled with high temperature globally during the warm season, especially for those regions with high probability of compound dry and hot events (figure 1(b)). Such a correlation favors the occurrence of compound dry and hot events, supporting previous studies that show a close relationship between the compound dry–hot event and precipitation–temperature dependence (Hao and Singh 2020). Additionally, similar patterns of the probability of compound events and precipitation–temperature correlation hold for precipitation and temperature without detrending (as shown in figures S4(a) and (b)), implying that the long-term trends of precipitation and temperature play a small role in their correlation, as shown by Zscheischler and Seneviratne (2017) for another period of 1870–1969. Furthermore, by assessing the distribution of scatter density of the probability of compound dry and hot events together with the correlation coefficient between precipitation and temperature, we find that higher probability is usually accompanied by a stronger negative precipitation–temperature correlation, highlighting that the related regions tend to face more compound dry and hot events (figures 1(c) and S4(c)). To better understand the potential impact of precipitation–temperature correlation on the probability of compound dry and hot events, the relationship is diagnosed using a linear regression model across the global land area, and relatively high explanatory power is found with a value of $0.89$ for 1982–2018, indicating that the probability of compound events is sensitive to the precipitation–temperature correlation.

As various patterns may exist in different regions, the probability of compound dry and hot events and precipitation–temperature correlation based on the spatial average of all grid cells over each of the eight subregions are calculated for comparison (figures 1(d) and S4(d)). Consistent with the above conclusions, high probability is prevalent in the region where the correlation coefficient between precipitation and temperature is strongly negative. On average, AUS has experienced the highest probability of compound dry and hot events with the strongest negative precipitation–temperature correlation, while AF has been hit by the lowest probability of compound dry and hot events with the weakest precipitation–temperature correlation. These indicate a high susceptibility of the region with the strongest negative precipitation–temperature correlation to the compound dry and hot events. In general, a high risk of compound events has been observed during recent decades across the globe, which might induce disproportionate socio-economic impacts, particularly for the aforementioned hotspots.

#### 3.2. Impacts of compound dry and hot events on global GPP

Before exploring the impact of compound dry and hot events on GPP, we first assess the correlation between GPP and SPI/STI (figure S5). A widespread positive GPP–SPI correlation exists, covering 86% of the global land area (only accounting for the region with GPP data) (figure S5(a)), indicating potentially negative impacts of droughts on GPP globally. Correspondingly, a widespread negative GPP–STI correlation occurs, where the area proportion is 81% (figure S5(b)), signifying that high temperature suppresses GPP in those regions. Similarly, for the spatial average, significant positive SPI–SGI correlation (at the 0.05 significance level) exists for global land, cropland, and pastureland areas, while negative STI–SGI correlation holds (figures 2(a) and (b)), which further confirms that both dry and hot conditions can decrease global GPP. Moreover, consistent patterns
Figure 1. The probability of compound dry and hot events and the correlation coefficients between precipitation and temperature during the warm season of 1982–2018. Maps of the probability of compound events (a), correlation between precipitation and temperature (i.e. corr (P, T)) (b), and their relationship (c). The spatial average of the probability of compound events and the precipitation–temperature correlation coefficients for the eight subregions (d). Those subregions include North America (NAM), South America (SAM), Europe (EU), Africa (AF), West Asia (WAS), East Asia (EAS), South Asia (SAS), and Australia (AUS). The panel in (b) is the percentage of the area with positive (P) and negative (N) correlation coefficients. $R^2$ in (c) is the explanatory power. The compound dry and hot events are defined as the seasonal precipitation $P$ below or equal to the 20th percentile in conjunction with the accompanying seasonal temperature $T$ above the 80th percentile.

are found in the scatterplots of the SPI, STI, and SGI (figures 2(d)–(f)). Indeed, a larger proportion of negative SGI values are scattered in the left quadrants with SPI < 0 in contrast to that of SPI > 0, while a larger proportion of positive SGI values are located in the lower quadrants with STI < 0 relative to that of STI > 0. In addition, we further investigate the conditional probability density function (PDF) of the SGI in response to different dry or hot conditions for the global land, cropland, and pastureland areas (figure S6). It is shown that negative values of the conditional means of the SGI exist for both dry and hot conditions, implying that the drying and warming conditions restrict the vegetation growth. Moreover, with the increase in the intensity of dry or hot events, the PDF curve shifts to the left, reflecting an increased risk of GPP reductions. Yet, droughts are observed to exert greater impacts on GPP than hot events, which agrees fairly well with the results of previous studies (Ciais et al. 2005, De Boeck et al. 2011, Chen et al. 2019).

For the probability of compound dry and hot events (denoted as the joint probability of precipitation and temperature using equations (1) and (2)), significant positive correlation is observed with the SGI (figure 2(c)), accounting for 86% of the global land area (figure 2(g)), which indicates a strong reduction in GPP under the high severity of compound dry and hot conditions across most of the globe. In addition, a relatively large proportion of negative SGI values scatter in the left upper quadrant (corresponding to SPI < 0 and STI > 0), suggesting a negative impact of compound dry and hot events on GPP (figures 2(d)–(f)). Further investigation has also been performed on the conditional probability of GPP reductions (i.e. SGI < 0) under individual dry, individual hot, and compound dry and hot conditions (figures 2(h) and S7). According to Lobell and Field (2007), bootstrap resampling is employed here to assess the uncertainty of the model with 1000 bootstrap samples, and one standard deviation is shown as the uncertainty range. By comparison, a broad consensus exists that a higher risk of GPP reduction occurs under compound dry and hot conditions than under individual dry or hot conditions. For example, the conditional probability of GPP reductions under different severity levels of compound dry and hot conditions increases by 8%–9% (this range indicates different severities of extremes) relative to that under the individual dry conditions, and it is 25%–42% compared with that under the individual hot conditions for the global land area. This further confirms the exacerbation of negative impacts on GPP induced by concurrent dry and hot events, which generally agrees with previous studies that showed greater negative impacts of compound drought and hot events on GPP than individual droughts or hot events (Zscheischler et al. 2014b, von Buttlar et al. 2018), as the concurrent droughts and hot events may exacerbate the stress of each other on the ecosystem. Specifically, evaporative cooling decreases under drought conditions; thus, this further increases the heat impact and, in return, intensifies the drought severity (De Boeck et al. 2011, AghaKouchak et al. 2014, von Buttlar et al. 2018).
To quantify the response of GPP to different severity levels of compound dry and hot events, we further assess the conditional probability density distribution of the SGI under three compound conditions (figures 2(i)–(k)). For all the scales of global land, cropland, and pastureland areas, the conditional mean of SGI is consistently negative under the three severity levels, demonstrating that compound dry and hot events suppress GPP globally. Additionally, this shift of the PDF of SGI to the left is more remarkable under more severe compound events, indicating that the enhanced severity of compound dry and hot conditions can further promote the reduction in GPP. Taking the global land area as an example, the conditional means of the SGI are −0.39, −0.62, and −1.01, respectively, corresponding to
those three conditions from abnormal to severe levels (figure 2(i)).

To quantify the response of GPP to compound dry and hot events, the annual mean anomalies of GPP under compound conditions are assessed over the period of 1982–2018 (figures 3 and S8). Negative GPP anomalies are found under compound dry and hot events in most regions of the globe, except for some high latitude regions where the warming temperature may favor vegetation growth (Zhao and Running 2010, Zhu et al 2021) (figures 3(a), S8(a) and (b)), consistent with the results shown by latitude zones (figures 3(b), S8(c) and (d)). This spatial pattern of a negative GPP anomaly resembles that obtained from the compound high vapor pressure deficit and low soil moisture events during 1871–1970 (Zhou et al 2019). Notably, these negative GPP anomalies are relatively remarkable in semi-arid, sub-humid, and humid regions (figures 3(c), S8(e) and (f)), where warm droughts play an important role in driving negative GPP extremes in large parts of these regions (Gampe et al 2021). For instance, the mean GPP anomaly due to moderate compound dry and hot events (i.e. SPI ≤ −0.8 & STI > 0.8) is −0.06, −0.27, −0.35, and −0.30 g C m⁻² d⁻¹ in arid, semi-arid, sub-humid, and humid regions, respectively. In addition, more severe compound dry and hot events usually lead to more significant negative GPP anomalies (figures 3(d)–(f)). In global cropland areas, for example, the mean GPP anomaly due to compound dry and hot events from the least to the most severe levels is −0.06, −0.10, and −0.15 g C m⁻² d⁻¹ (figure 3(e)). These results indicate that ecosystem productivity is vulnerable to compound dry and hot events globally with varying magnitudes of response across regions. Additionally, generally consistent results have been found for these two GPP datasets, indicating the relative robustness of such findings.

3.3. Impacts of compound dry and hot events on regional GPP

As impacts of climate extremes on GPP may differ geographically, we further compare the conditional probability of GPP reductions (i.e. SGI < 0) under individual dry, individual hot, and compound dry and hot conditions for the eight subregions (figure 4). In general, further exacerbation of the risk of GPP reductions under the compound dry and hot conditions occurs for all the subregions in comparison to the individual hot or individual dry conditions. Specifically, the increase in the conditional probability of GPP reductions ranges from 0.06 to 0.10 over the eight regions when the hot conditions transform to the compound dry and hot conditions, with AF
and AUS showing a relatively high increase of 0.10. Similarly, this increase ranges from 0.01 to 0.10 when the dry conditions aggravate into the compound dry and hot conditions over the eight regions, with EU undergoing the highest increase in magnitude of 0.10. It should be noted that the EAS has a relatively low increase in probability under compound events compared to the individual dry conditions. This may be due to the fact that the warming climate can promote vegetation growth in certain northern high latitudes as the current temperature is usually lower than the optimum, which may mitigate the adverse effect of droughts (Zhao and Running 2010, Zhu et al 2021). Yet, the positive correlation between GPP and the STI in northern EAS further supports this finding (figure S5(b)). Additionally, most regions, including SAM, AF, EAS, SAS, and AUS, show higher risks of GPP reductions under the individual dry conditions than the hot conditions, highlighting the remarkably negative response of GPP to dry events, which agrees with the aforementioned global-scale results. Similar patterns are obtained based on the other thresholds of the SPI and STI (as shown in figures S9 and S10). Overall, under disproportionate impacts of climate events, these results suggest that GPP is more vulnerable to compound dry and hot events than to individual dry or hot events across the globe.

In addition, further analyses are performed for the conditional probability of SGI < 0 under different severity levels of compound dry and hot events for the eight subregions (figure 5). An increase in the conditional probability of GPP reductions dominates
all eight regions with the intensified severity of compound dry and hot events. For instance, the conditional probability of SGI < 0 under the abnormal compound dry and hot events (i.e. SPI = −0.5 & STI = 0.5) in SAM is 0.60, and it climbs to 0.66 and 0.75 under the moderate (i.e. SPI = −0.8 & STI = 0.8) and severe (i.e. SPI = −1.3 & STI = 1.3) compound conditions, respectively. Therefore, an upward trend in the risk of GPP reductions holds across the global land area with the increased severity of compound dry and hot events.

4. Discussion

4.1. Compound meteorological conditions from a dependence perspective

Precipitation and temperature usually covary negatively during the warm season (Trenberth and Shea 2005, Hao and Singh 2020), as further confirmed by this study, thus favoring concurrent dry and hot events. It has consistently been shown that the warming climate increases the risk of droughts and finally the likelihood of compound dry and hot extremes (AghaKouchak et al 2014, Diffenbaugh et al 2015). This is mainly due to the fact that the precipitation deficit directly induces dry soils and, in turn, less evaporative cooling and convective cloud formation and eventually a higher temperature that can generate a higher evapotranspiration rate, and further intensifies the dry conditions (Fischer et al 2007, De Boeck and Verbeeck 2011, Wang et al 2021a).

Conversely, evaporative cooling can partly dampen the rise in temperature if there is an adequate water supply (von Buttlar et al 2018). On this basis, taking only one variable into account is incomplete for risk assessment of climate extremes, especially for those events that include multiple contributing variables, such as compound dry and hot events. Overall, our study underscores the dominant role of precipitation–temperature dependence on the risk of compound dry and hot events during the warm season across the globe. Additionally, it should be pointed out that the precipitation–temperature dependence will strengthen in the 21st century, and thus there will be more frequent compound dry and hot events worldwide (Zscheischler and Seneviratne 2017), which may lead to more stress on various sectors, including terrestrial ecosystems. Notably, the long-term trend of precipitation and temperature is projected to play an important role in driving the variations of compound dry and hot events during 2001–2100, unlike the historical period 1870–1969 in which a small role is observed (Zscheischler and Seneviratne 2017). Importantly, devastating compound threats may be caused, even if the driving events or variables are not extreme (Seneviratne et al 2012). Therefore, more effort is needed to mitigate the risk of compound hazards.

4.2. Response of vegetation to climate extremes

This investigation demonstrates the enhanced impact of compound dry and hot events on global GPP during the warm season. Compared with other seasons, extreme events that occur during the warm season generally contribute a large proportion to the GPP variation (Chen et al 2019, Wang et al 2021a). This is because the highest GPP usually matches with the warm season, accordingly resulting in a relatively high absolute GPP anomaly when climate extremes occur in that time (Chen et al 2019). Considering that the warm season is closely related to the main growing season (Zhou et al 2019), exploration of the response of GPP to the compound extreme during that time is vital in understanding the variation of GPP. We also investigate the response of GPP to compound events during the hottest month globally (figure S11), and generally consistent negative impacts of compound dry and hot events on GPP have been observed.

In this study, the negative impacts of individual droughts and hot events on GPP have firstly been diagnosed. This coincides with existing studies that showed the remarkably negative response of GPP to droughts or hot events (Ciais et al 2005, Zscheischler et al 2014a, Xu et al 2019). We also find that dry events generally put a greater stress on GPP than hot events, which is consistent with previous evidence that droughts can largely decrease GPP (Zscheischler et al 2014a, Chen et al 2019). Furthermore, in agreement with recent findings that showed negative impacts of compound events on regional GPP (Chen et al 2019, Zhu et al 2021), we find a stronger reduction in GPP caused by compound dry and hot events than individual dry or hot events globally. The high temperature can directly impact photosynthesis and respiration by influencing enzyme activities, while droughts can impact the water availability of vegetation, thereby regulating ecosystem productivity and leading to a reduction in land carbon sink (von Buttlar et al 2018, Zhu et al 2021), especially for ecosystem types with shallow root systems, such as pasture and crop (Reichstein et al 2013, Lesk et al 2016). Additionally, although high CO\textsubscript{2} concentration is conducive to vegetation production, extreme high temperatures and droughts can reduce GPP widely (Long et al 2004, Ciais et al 2005, Xu et al 2019, Wang et al 2020).

As multiple lines of evidence also show that the lag or legacy effect of climate events on vegetation is widespread (Anderegg et al 2013, Frank et al 2015, Huang et al 2016), further analysis on the relationship between the warm season GPP and its antecedent SPI/STI/the probability of compound dry and hot events ahead of 1–3 months has been carried out based on Pearson correlation coefficients (figures S12 and S13). Consistent patterns have been found with that of no time lag, especially for the 1 month time lag,
with which the percentage of areas with significant positive correlation coefficients between GPP and the probability of compound dry and hot events is close. Correspondingly, the value of the percentage area at the 0 month and 1 month lag is 45% and 43%, respectively, based on the mean of the NIRv and LUE GPP data. The percentage area at the 1 month time lag (27%) based on the NIRv dataset is even larger than that at the 0 month time lag (24%). In addition, this lag effect decreases with the increase in lag time. Altogether, these results indicate that vegetation productivity during the warm season may be affected by the antecedent compound dry and hot events. Note that the risk of compound dry and hot events is projected to increase under future climate change (Zscheischler and Seneviratne 2017, Wu et al 2021) and, as a consequence, severe ecosystem damage could be caused across the globe, which calls for more efforts to reduce the potential impacts. Overall, the findings in this study emphasize the need to consider the risk of compound dry and hot events when devising adaptation and mitigation strategies.

4.3. Uncertainties, limitations, and extensions
Based on the meta-Gaussian model, this study provides a probabilistic assessment of the response of GPP to compound dry and hot events globally. A level of uncertainty exists. For example, the complicated interaction between GPP and climate variables, such as the tail dependence among the climate variables (Hao et al 2016, Zscheischler et al 2017, Zscheischler and Seneviratne 2017), has not been considered. In addition, two GPP datasets are used in this analysis, and generally consistent results are found. Still, uncertainties may exist, as Advanced Very High Resolution Radiometer (AVHRR) data have certain systematic biases due to the unstable orbits and records before 2000 (Frankenberg et al 2021), as well as the fact that inconsistent approaches are used to estimate LUE when modeling GPP across different datasets (Wei et al 2017). There is thus a need to conduct the analysis using more GPP datasets to further assess the uncertainty. In addition, due to the lack of long-term and large-scale observations of GPP, a thorough investigation of their response to the changing climate is partly limited.

In addition to the precipitation–temperature dependence discussed in this study, the soil moisture and vapor pressure deficit play an important role in driving the dryness stress on limiting ecosystem production (Zhou et al 2019, Liu et al 2020). Other factors, such as land surface feedback and atmospheric circulation dynamics, may contribute to the change in the likelihood of dry and hot events during the warm season (Seneviratne et al 2010, Zscheischler and Seneviratne 2017, Hao and Singh 2020). Thus, besides the direct precipitation–temperature relationship, a deep understanding of the physical mechanism of the variations of dry and hot extremes is also critical for the development of measures to mitigate the potential impacts, which is beyond the scope of this study.

Furthermore, land use and land cover changes also play an important role in the terrestrial carbon budget, such as rapid urban expansion, which has been revealed to reduce the terrestrial net primary productivity, eventually threatening food security (Liu et al 2019). In this regard, more effort is needed to estimate the relative effects of compound extremes and land cover changes on the variation of terrestrial GPP. Finally, a notable influence of human activities on cropland has been observed, such as irrigation, which has a cooling effect and can reduce hot events (Lobell et al 2008, Sacks et al 2009), thus leading to the reduction of compound dry and hot events. Hence, evaluation of the influence of human activities on cropland may improve our understanding, which is required in future work.

5. Conclusions
Despite various reports addressing the individual effects of dry or hot events on terrestrial GPP, to our knowledge, few investigations have focused on the effects of compound dry and hot events so far. Here, we assess the probabilistic impact of compound dry and hot events on GPP at both global and regional scales, including crop and pasture ecosystems, during the warm season from 1982 to 2018. Together, the conditional probability of GPP reduction has been analyzed under different individual dry, hot, and compound dry and hot conditions based on the meta-Gaussian model. The results demonstrate that the region with strongly negative precipitation–temperature correlation is prone to the occurrence of compound dry and hot events, with negligible effects of the long-term trends of precipitation and temperature, which puts increasing negative stress on GPP with the intensified severity of compound conditions across the globe. In addition, compound dry and hot events tend to promote further reductions in GPP globally relative to individual dry or hot events. Indeed, the conditional probability of global GPP reduction under compound dry and hot conditions increases by 8%–9% (25%–42%) compared with that under individual dry (hot) conditions. Our results highlight the sensitivity of GPP to compound dry and hot conditions globally.

Data availability statement
The data that support the findings of this study are openly available at the following URL/DOI: www.cru.uea.ac.uk/data.
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