Probabilistic assessments of the impacts of compound dry and hot events on global vegetation during growing seasons

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Abstract

The response of vegetation to climate extremes, including droughts and hot extremes, has been evaluated extensively in recent decades. However, quantitative assessments of individual and combined impacts of dry and hot conditions on vegetation are rather limited. In this study, we developed a multivariate approach for analyzing vegetation responses to dry, hot, and compound dry-hot conditions from a probabilistic perspective using precipitation, temperature, and the Normalized Difference Vegetation Index (NDVI) for the period from 1982 to 2015. The Standardized Precipitation Index (SPI) and Standardized Temperature Index (STI) were used to define individual and compound dry and hot conditions. Based on the diagnosis of the correlation between SPI/STI and NDVI during growing seasons, we investigated the conditional probability of vegetation decline under different climate conditions. The results showed that vegetation was affected by compound dry and hot conditions (defined as SPI $\leq -1.3$ and STI $>1.3$) in arid and semi-arid regions. In these regions, the conditional probabilities of vegetation decline under compound dry and hot conditions increased by 7% and 28% compared with those under individual dry and hot conditions, respectively. The impact of compound dry and hot events on vegetation for different biomes was also assessed. Temperate grassland was found to be particularly vulnerable to compound dry and hot conditions. This study highlights the necessity of considering compound dry and hot extremes when assessing vegetation responses to climate extremes under global warming.

1. Introduction

Vegetation is a key component of the terrestrial system and may affect climate conditions, carbon balance, and the water cycle (Nemani et al 2003, Gentine et al 2019, Linscheid et al 2020, Piao et al 2020). It is vulnerable to weather and climate extremes such as droughts and heatwaves, which may affect different processes, including photosynthesis, respiration, and carbon use, leading to biomass decline and mortality (Sippel et al 2018, Piao et al 2019). Under global warming, drought and heat-related extremes have been shown to increase in frequency and spatial extent (Counou et al 2013, Hao et al 2013), posing serious threats to ecosystems. It is thus important to understand ecosystem responses to climate extremes, including droughts and heat extremes in the context of global warming.

Previous studies have evaluated the impact of dry and hot extremes (or precipitation and temperature) on vegetation based on deterministic and probabilistic approaches. The impact of droughts on vegetation has been studied based on drought indicators (e.g. Standardized Precipitation Index (SPI)) and vegetation indicators (e.g. Normalized Difference Vegetation Index (NDVI)) across the globe (Xu et al 2011, 2012, Vicente-Serrano et al 2013, He et al 2017, Papagiannopoulou et al 2017, Zhao et al 2017, Zhang and Zhang 2019, Deng et al 2020). Liu et al (2013) assessed the sensitivity of global vegetation to climate extremes and found that extreme low precipitation had the highest impacts on vegetation.
among different variables (particularly for temperate broadleaf forest and temperate grassland). Papagiannopoulou et al (2017) investigated the environmental control on vegetation based on multi-decadal satellite data records and found that water availability was the dominant driver of vegetation at the global scale (about 61% of vegetated surfaces). Meanwhile, high-temperature anomalies have been shown to affect vegetation growth by influencing plant metabolism and cell integrity (Baumbach et al 2017, Wu et al 2019, Wen et al 2019a, Li et al 2021). For example, Karnieli et al (2010) evaluated the relationship between land surface temperature (LST) and NDVI over the North American continent. They found positive LST-NDVI correlations when energy is the limiting factor for vegetation growth (e.g. higher latitude regions and the beginning of growing seasons) and negative LST-NDVI correlations when water is the limiting factor (e.g. low latitudes and the midseason). In recent decades, several studies have assessed the responses of vegetation to climate extremes from probabilistic perspectives based on joint or conditional distribution models (Jha et al 2019, Fang et al 2019a, 2019b). Fang et al (2019b) quantified drought impacts on terrestrial vegetation dynamics based on the NDVI in mainland China using the copula approach and found that the average probability of vegetation decline given drought conditions was higher in central Inner Mongolia.

Although extensive studies have been devoted to evaluating the impact of dry and hot extremes on vegetation growth at regional and global scales, they mainly evaluated the impact of these factors separately. Due to the interaction between dry and hot conditions, the concurrent or consecutive occurrence of these events (i.e. compound dry and hot events) may cause larger impacts than individual extremes (Hao et al 2013, Zscheischler and Seneviratne 2017, Zhou and Liu 2018, Ribeiro et al 2020b). Consequently, recent decades have witnessed a surge in the study of compound dry and hot events and their impacts on vegetation (Sippel et al 2018, von Buttlar et al 2018, Hao et al 2020). For example, based on SPI and Standardized Temperature Index (STI), Zscheischler et al (2014) compared impacts of different climate extremes on Carbon fluxes and found that compound dry and hot conditions had larger impacts on Carbon fluxes than individual dry or hot conditions. Rammig et al (2015) assessed coincidence rates of climate extremes (e.g. water stress) and anomalous vegetation activity and found that low precipitation and high temperature (or their combinations) occur in years with 28% of tree ring width indices below two standard deviations. Although the impacts of dry and hot conditions on vegetation have been emphasized, quantitative assessments of vegetation responses to separate and combined dry and hot events are rather limited.

The objective of this study was to quantify the response of global vegetation (represented by NDVI) to individual and combined dry and hot conditions during growing seasons from a probabilistic perspective. Based on the SPI and STI to represent dry and hot conditions (Zscheischler et al 2014), we derived the conditional distribution of NDVI under individual and compound dry and hot conditions by constructing the trivariate distribution function. The probabilistic responses of vegetation decline under individual dry conditions, hot conditions, and compound dry and hot conditions were then assessed. The response of different vegetation types to compound dry and hot events was also discussed.

2. Data and method

2.1. Data

Gridded monthly precipitation, temperature, and potential evapotranspiration data from January 1982 through December 2015 with a spatial resolution of 0.5° × 0.5°, covering the global land surface (excluding Antarctica) were used in this study. This dataset was obtained from the Climate Research Unit at the University of East Anglia. The NDVI is a remote sensing-based index to measure vegetation conditions. The biweekly NDVI data derived from NOAA Advanced Very High Resolution Radiometer instruments from 1982 to 2015 at 1/12° resolution were obtained from the Global Inventory Monitoring and Modeling System. This is a long-term record of remotely sensed-NDVI and has been widely used for the analysis of the relationships between climate and vegetation response (Wu et al 2015, Nicolai-Shaw et al 2017). To match the temporal and spatial resolution of climate data, the NDVI data were transformed to a monthly time scale through the maximum value composite method and regridded to 0.5° × 0.5° resolution. Meanwhile, we masked out the area with very low NDVI values (long-term mean NDVI in growing seasons is less than 0.1) (Zhao et al 2018).

We focused on the growing season and only considered NDVI data during April–October in the area of 20° N–70° N, October–April in the area of 20° S–60° S, and January–December in the area of 20° S–20° N (Zhao et al 2018). The SPI and STI were computed based on the precipitation and temperature of the growing season. Specifically, the time scales (or accumulation periods) of SPI and STI for growing seasons of the three regions are seven months, seven months, and twelve months, respectively. The responses of vegetation to extreme events for different biomes (figure S1 (available online at stacks.iop.org/ERL/16/074055/mmedia)) were assessed based on the terrestrial ecoregions from Terrestrial Ecoregions of the World (Olson et al 2001).
2.2. Indicators for climate extremes and vegetation

The SPI and STI were employed in this study to track dry and hot conditions, respectively (Zscheischler et al. 2014, Feng et al. 2019). These two indicators were derived by fitting a marginal distribution (empirical Weibull distribution) to obtain the marginal probability, which was then transformed into standard variables based on the standard normal distribution. Following U.S. Drought Monitor (Svoboda et al. 2002), we used the SPI value of \(-1.3\) to represent severe drought conditions. Similarly, the threshold of 1.3 for the STI was used to define hot conditions (Feng et al. 2019). The compound dry and hot condition was defined as the concurrence of low SPI and high STI (SPI \(\leq -1.3\) and STI \(> 1.3\)). Other thresholds (e.g. SPI \(\leq -0.5\) and STI \(> 0.5\), SPI \(\leq -0.8\) and STI \(> 0.8\)) were also used and the results were consistent (not shown). To facilitate statistical modeling, we defined the Standardized Normalized Difference Vegetation Index (SNDVI) to track the vegetation condition (i.e. SNDVI < 0 indicates a reduction of vegetation activity).

Furthermore, we used the Aridity Index (AI) (AI = MAP/MAE) to reflect the annual dry and humid conditions across the world, where MAP and MAE represent mean annual precipitation and mean annual potential evapotranspiration, respectively. We focused on the four climate regions defined based on AI (figure S2), including the arid region (0.03 \(\leq\) AI < 0.2), semi-arid region (0.2 \(\leq\) AI < 0.5), semi-humid region (0.5 \(\leq\) AI < 0.65), humid region (AI \(\geq 0.65\)) (Yuan et al. 2017).

2.3. Method

The dependence between climate indicators (SPI and STI) and vegetation (SNDVI) was evaluated based on the correlation analysis. To model the dependence among vegetation and climate indicators, multivariate and conditional distributions can be utilized to estimate the probabilistic response of vegetation under different extreme conditions from a statistical perspective (e.g. copula or vine copula models) (Feng et al. 2019, Jha et al. 2019, Fang et al. 2019a, 2019b, Ribeiro et al. 2020a). Following Feng et al. (2019), the joint distribution of vegetation and climate indicators was estimated from the meta-Gaussian model, which captures dependence among multivariate variables and allows for flexible forms of marginal distributions (Kelly and Krzysztofowicz 1997, Hao et al. 2018). For two continuous random variables \(X_1\) and \(X_2\), we can obtain two standardized normal random variables \((Z_1\) and \(Z_2\)) based on the Normal Quantile Transformation. As a result, the bivariate joint distribution of the meta-Gaussian model can be expressed as (Kelly and Krzysztofowicz 1997):

\[
P(Z_1 \leq z_1, Z_2 \leq z_2) = \int_{-\infty}^{z_1} \int_{-\infty}^{z_2} \frac{1}{2\pi \sqrt{1-\rho^2}} \exp \left( -\frac{z_1^2 - 2\rho z_1 z_2 + z_2^2}{2(1-\rho^2)} \right) \, dz_1 \, dz_2 \tag{1}
\]

where \(\rho\) is the Pearson’s correlation coefficient between \(Z_1\) and \(Z_2\); \(z\) and \(t\) are the integral variables.

To evaluate the response of vegetation to dry and hot conditions, the conditional distribution in the trivariate case was used to estimate the probability of vegetation given different levels of dry and hot conditions. This can be obtained by extending the joint probability to the three dimensions. In this study, we were particularly interested in the vegetation decline (defined as SNDVI < 0). Thus, the conditional probability \(P(\text{SNDVI} < 0|\text{SPI} \leq -1.3, \text{STI} > 1.3)\), \(P(\text{SNDVI} < 0|\text{SPI} \leq -1.3, \text{STI} > 1.3)\), and \(P(\text{SNDVI} < 0|\text{SPI} \leq -1.3, \text{STI} > 1.3)\) can be derived to estimate the impact of dry, hot, and compound dry-hot conditions on vegetation decline. Following Ribeiro et al. (2020a), the conditional probability of vegetation decline given individual dry, individual hot, and compound dry and hot condition can be expressed as:

\[
P(\text{SNDVI} < 0|\text{SPI} \leq -1.3) = \frac{P(\text{SNDVI} < 0, \text{SPI} \leq -1.3)}{P(\text{SPI} \leq -1.3)} \tag{2}
\]

\[
P(\text{SNDVI} < 0|\text{STI} > 1.3) = \frac{P(\text{SNDVI} < 0, \text{STI} > 1.3)}{1 - P(\text{STI} \leq 1.3)} \tag{3}
\]

\[
P(\text{SNDVI} < 0|\text{SPI} \leq -1.3, \text{STI} > 1.3) = \frac{P(\text{SNDVI} < 0, \text{SPI} \leq -1.3) - P(\text{SNDVI} < 0, \text{SPI} \leq -1.3, \text{STI} \leq 1.3)}{P(\text{SPI} \leq -1.3) - P(\text{SPI} \leq -1.3, \text{STI} \leq 1.3)} \tag{4}
\]

Note that if we assume statistical independence between climate extremes and vegetation, the conditional probability of the SNDVI < 0 is expected to be 0.5 (i.e. SNDVI follows the standard normal distribution). A positive (negative) impact of extremes on vegetation is expected to lead to a decreased
(increased) probability of vegetation decline through comparisons with the probability of the independent case (0.5).

3. Results

3.1. Correlation analysis for different regions
To show the interaction between climate conditions and vegetation during growing seasons, correlation coefficients between the SNDVI and SPI (STI) from 1982 to 2015 are shown in figure 1 (significant correlation coefficients at the 0.05 significant level are shown in figure S3). For northern high latitude regions, the correlation between the SNDVI and SPI is not significant, while that between the SNDVI and STI is mostly positive. This is consistent with previous studies showing that precipitation–vegetation correlations are relatively weak for cold regions, while positive temperature–vegetation correlations are generally present in these areas (e.g. Eurasian tundra or high latitudes regions) (Karnieli et al 2010, Wu et al 2015). A possible reason for the dependence pattern in these high latitude regions is that vegetation growth is mainly influenced by energy (or temperature) (Nemani et al 2003, Papagiannopoulou et al 2017). In tropical regions, complicated correlation

Figure 1. Correlation coefficients between vegetation (SNDVI) and dry/hot indicators (SPI/STI) during growing seasons from 1982 to 2015. (a) Correlations between SPI and SNDVI. (b) Correlations between STI and SNDVI.
patterns between climate variables and vegetation are shown. For example, positive STI-SNDVI correlations exist in certain regions, such as central Africa and northern South America, while negative STI-SNDVI correlations are shown in northeast South America. These correlation patterns may be related to different vegetation types and the critical role of radiation in the tropics (Nemani et al. 2003, Zhao et al. 2018, Wen et al. 2019a).

Figure 1 also shows positive correlations between SNDVI and SPI in central North America, southern South America, southern Africa, central Eurasia, and Australia, most of which are arid and semi-arid regions. In addition, a negative SNDVI-STI correlation is shown for most of these regions. These correlation patterns imply that vegetation is affected by both dry conditions and hot conditions (or their combinations) in arid and semi-arid regions, which are generally consistent with previous studies (Zeng et al. 2013, Wu et al. 2015, Zhao et al. 2018, Xie et al. 2019, Wen et al. 2019a). An explanation may be that water availability is the restricted condition for vegetation activity in arid and semi-arid regions and biomes react rapidly when water deficits occur (Ichii et al. 2002, Fensholt et al. 2012, Vicente-Serrano et al. 2013, He et al. 2018, Fang et al. 2019a). In these regions, warm temperatures and accompanying high evapotranspiration may result in a soil moisture deficit and further aggravate the severity of dry conditions, leading to simultaneous occurrences of dry and hot extremes that influence vegetation growth (Zscheischler et al. 2015, Zscheischler and Seneviratne 2017, Hao et al. 2018, Sippel et al. 2018, Miralles et al. 2019). Over global land areas, the concurrence of positive SNDVI-SPI and negative SNDVI-STI correlations was shown in 31.06% of all grid points (significant correlations are shown in 6.44% of all grid points). These results highlight the importance of considering the concurrent impacts of droughts and hot extremes on vegetation.

Figure 2 shows boxplots of correlation coefficients for four different climate regions (arid, semi-arid, semi-humid, and humid regions). For humid regions (including areas of tropical rainforest and high latitude of the northern hemisphere), 75.13% of grid points showed a positive relationship between the SNDVI and STI (with a median of 0.23), while the correlation coefficients between the SNDVI and SPI range from −0.73 to 0.75 (with a median of 0.02), which reflects the complex relationship between dry conditions and vegetation in these regions (Wen et al. 2019a). For the arid (and semi-arid) regions, the median of the SNDVI-SPI correlation is 0.27 (0.35) and that of the SNDVI-STI correlation is −0.17 (−0.13). These results indicate that vegetation in these regions is affected by dry and hot conditions, and thus both factors need to be considered in evaluating the relationship between climate variability and vegetation. For semi-humid regions, positive SNDVI-SPI correlations are shown (with a median of 0.17) with complex correlation patterns between SNDVI and STI (i.e. with a median of 0.08).
3.2. Vegetation changes under individual dry and hot conditions

Based on the correlation analysis, we then employed the proposed model for the probabilistic analysis of the impact of compound dry and hot events on vegetation. We showed the results at one grid (21.25° E, 28.75° S) in southern Africa to illustrate the application of the proposed model. For the selected grid, the meta-Gaussian model was built to fit the SPI, STI, and SNDVI. The scatterplots of the simulated and observed SPI-STI, SPI-SNDVI, and STI-SNDVI correlations are shown in figures 3(a)–(c). A negative correlation exists for the SPI-STI and STI-SNDVI pairs, while a positive correlation is shown for SPI-SNDVI. Based on the proposed model, the simulated pairs of SPI, STI, and SNDVI are shown in figure 3(d). The consistent pattern of dependence structures for simulation and observation indicates that the proposed model generally performs well in modeling dependence among the SPI, STI, and SNDVI. Additionally, the empirical and theoretical estimations of the joint probability of SPI-STI, SPI-SNDVI, and STI-SNDVI are shown in figure S4, which confirms the overall good performance of the proposed model for this grid point. The meta-Gaussian model was then applied to assess the impacts of compound dry-hot conditions on vegetation. Following Ribeiro et al. (2020a), the joint probabilities of the vegetation decline given different levels of dry and hot conditions are shown in figure 3(d). The results indicate an increase in vegetation decline with the increased severity of the compound dry-hot condition for this grid.

The conditional probabilities of SNDVI < 0 given individual dry conditions (SPI ≤ −1.3) and individual hot conditions (STI > 1.3) during growing seasons are shown in figures 4(a) and (b), respectively. In high latitude regions, the conditional probability of vegetation decline given dry conditions is close to the probability of the independent case. These results demonstrate that vegetation in this region is not significantly dependent on precipitation. Meanwhile, hot conditions lead to a lower probability of vegetation decline (<0.5). An explanation is that temperature is the limiting factor in biomass production in high latitude regions, and sufficient heat conditions have positive effects on vegetation during growing seasons. For certain tropical regions (such as the Amazon area), a slight increase in the conditional probability for vegetation decline given dry conditions is observed. The probability is generally higher than that of the independence case (0.5), demonstrating the effects of dry conditions on vegetation growth in tropical regions. For large regions in central North America, southern South America, southern Africa, central Eurasia, and Australia, higher conditional probabilities of vegetation decline (>0.5) given dry or hot conditions are observed. These results...
Figure 4. The conditional probability of vegetation decline ($\text{SNDVI} < 0$) given individual dry conditions (a), individual hot conditions (b), and compound dry-hot conditions (c) during growing seasons from 1982 to 2015.

Figure 5. Conditional probability of vegetation decline given dry conditions, hot conditions, and compound dry-hot conditions over four climate regions during growing seasons from 1982 to 2015.

indicate that increased dry conditions or heat stresses induce an increased probability of vegetation decline in these regions.

Figure 5 demonstrates, via boxplots, the conditional probability of vegetation decline over different climate regions. These probability patterns are closely related to the correlation pattern in section 3.1. Specifically, the positive (negative) correlation between SPI and SNDVI indicates a higher (lower) likelihood of vegetation reduction under dry conditions. Similarly, the positive (negative) STI-SNDVI correlation indicates a lower (higher) likelihood of vegetation decrease under high temperatures. For example, for humid regions (medians of SPI-NDVI and STI-NDVI correlations are 0.01 and 0.23), the median conditional probabilities of $P(\text{SNDVI} < 0|\text{SPI} \leq -1.3)$ and $P(\text{SNDVI} < 0|\text{STI} > 1.3)$ are 0.51 and 0.32, respectively. This indicates that the median of the probability of vegetation decline given dry conditions is close to...
the independent case, and that given hot condition is lower than that of the independent case. In contrast to humid regions, higher conditional probabilities of vegetation decline given dry or hot conditions are shown in arid and semi-arid regions. The median conditional probabilities of individual dry and hot conditions are 0.70 and 0.62 in arid regions (0.75 and 0.60 in semi-arid regions), which are considerably higher than those of the independent case, indicating that vegetation in these arid regions is affected by dry and hot conditions (Ji and Peters 2003, Kalisa et al 2019).

3.3. Vegetation change under compound dry and hot conditions
To illustrate the impact of both dry and hot conditions on vegetation, we also computed the conditional probability of vegetation decline (SNDVI < 0) under combined water and heat stresses (i.e. SPI \(\leq -1.3\) and STI > 1.3), and compared it with that from individual dry and hot conditions. The conditional probability \(P(\text{SNDVI} < 0 | \text{SPI} \leq -1.3, \text{STI} > 1.3)\) during growing seasons at the global scale is shown in figure 4(c). For high latitude regions, there is a substantial decrease in the probability of vegetation decline given compound dry and hot conditions compared with individual dry conditions. This is because, with weak SPI-NDVI correlations in these regions, hot conditions could favor vegetation growth, reducing the probability of vegetation decline. For large regions in central North America, southern South America, southern Africa, central Eurasia, and Australia, the conditional probability of vegetation decline under compound dry and hot conditions is relatively higher than that under individual dry or hot conditions (figure S5).

For the four climate divisions, the conditional probability of vegetation decline is relatively higher in arid and semi-arid regions (compared with the humid region) since the vegetation in these regions is influenced by dry conditions as well as heat stresses. Specifically, the medians of conditional probabilities of vegetation decline given SPI \(\leq -1.3\) and STI > 1.3 in the arid, semi-arid, semi-humid, and humid regions are 0.77, 0.78, 0.56, and 0.34, respectively. For all grid points in arid and semi-arid regions, the average of the conditional probabilities under dry conditions, hot conditions, and compound dry-hot conditions are 0.73, 0.61, and 0.78, respectively. These results indicate that the probability of vegetation decline under compound dry-hot conditions increased by approximately around 7% and 28%, respectively, compared with that under individual dry and hot conditions, in arid and semi-arid regions.

3.4. Impacts of compound dry and hot event on different vegetation types
Due to the differences in the physiological structure of vegetation, the sensitivity and vulnerability of ecosystems are expected to vary for different dry and hot conditions (Komatsu et al 2007, Liu et al 2013, He et al 2015, Zhang et al 2015, Gazol et al 2016). In this section, we discuss differences in the response of major vegetation types to extreme events, with focus on forest and grassland ecosystems. To demonstrate the relationship between climate conditions and different vegetation types during growing seasons, boxplots of correlation coefficients for SNDVI and SPI (STI) for different vegetation types are shown in figure 6(a). In addition, the conditional probabilities of vegetation decline under dry or hot conditions for different vegetation types are shown in figure 6(b).

For the forest ecosystem, a wide range of the correlation patterns between SPI and SNDVI is shown. Slightly positive correlations between the SPI and SNDVI are observed for tropical/subtropical forests and temperate broadleaf forests (the medians of the correlation coefficients are 0.08), as shown in figure 6(a). Meanwhile, negative SPI-SNDVI correlations are shown in several areas, such as certain Amazon regions, which is likely due to the reason that high temperature and radiation during dry periods can promote photosynthesis (Hilker et al 2014, Zhao et al 2017, Zhang and Zhang 2019). The median probabilities of vegetation decline given dry conditions for the tropical and subtropical forests and temperate broadleaf forests are 0.56 (slightly higher than that of the independent case). The SPI-SNDVI correlation for the temperate coniferous forest is close to zero (with a median of \(-0.03\)), and the conditional probability under drought conditions is complex without a clear pattern. Regarding the correlations between the STI and SNDVI in forest ecosystems, we found that large portions of grid points presented positive correlations. This positive STI-SNDVI correlation in the temperate forest is generally higher than that in the tropical and subtropical forests, as shown in figure 6(a). Accordingly, a lower probability of vegetation decline (<0.5) given hot conditions is found for temperate coniferous forests and temperate broadleaf forests (e.g. probabilities are 0.33 and 0.37, respectively) (see figure 6(b)). This is consistent with previous studies that hot extreme can promote vegetation production during growing seasons for temperate forest ecosystems (Zscheischler et al 2014, Wu et al 2015, Zhang et al 2015, Papagiannopoulou et al 2017). Given compound dry and hot conditions, a large portion (59.78%) of temperate coniferous forests and temperate broadleaf forests shows a low probability of vegetation decline (<0.5), which mainly resulted from the overall positive STI-SNDVI relationship (and a weak SPI-SNDVI correlation).

Grassland ecosystems are sensitive to spatial-temporal changes in climate factors such as temperature and precipitation (Seddon et al 2016). We found that large portions of grid points presented
positive correlations between the SPI and SNDVI for tropical and subtropical grasslands and temperate grasslands, as shown in figure 6(a) (e.g. medians of SPI-SNDVI correlations for the two ecosystems are 0.26 and 0.25, respectively). The SPI-SNDVI correlation for grasslands is generally much stronger than for forests. Accordingly, the probability of vegetation decline for the tropical and subtropical grasslands and temperate grasslands under dry conditions is much higher than that of the independent case (with a median of 0.69 and 0.68, respectively). A possible reason is that, compared to forests, grasslands obtain water from a shallower soil layer (thus vulnerable to water stress); while trees have greater drought adaptation abilities due to their access to water at deeper depths (Nicolai-Shaw et al 2017, Zhang and Zhang 2019). The STI-SNDVI correlation over large portions of grid points is negative for temperate grasslands, and the probability of vegetation decline given hot conditions is 0.55, which is slightly higher than that of the independent case. The relationship of STI and SNDVI for tropical and subtropical grasslands is close to the independent case. Under compound dry and hot conditions, large regions of grasslands show a higher probability of vegetation decline than that under individual dry or hot conditions. For example, the medians of conditional probabilities of vegetation decline given dry, hot, and compound dry-hot conditions are 0.68, 0.55, and 0.70, respectively, for temperate grasslands (see figure 6(b)). Furthermore, we notice the highest probability under compound dry and hot events is shown for temperate grasslands among all the vegetation types. These results indicate a high risk of vegetation loss for grassland ecosystems.
under compound dry and hot conditions, especially for temperate grasslands.

Following the studies by Ribeiro \textit{et al} (2020a), the changes in the probability of vegetation decline from individual dry (hot) conditions to compound dry-hot conditions (SPI $\leq -1.3$ and STI $> 1.3$) imply the relative impact of hot (dry) conditions on vegetation. For example, the probability of vegetation decline given dry conditions, hot conditions, and compound dry-hot conditions for temperate conifer forests are 0.47, 0.33, and 0.34. Accordingly, the change of vegetation decline from dry to compound dry-hot conditions is $-0.13$ and from hot to compound dry-hot conditions is 0.01. This indicates that the relative impact of hot conditions on temperate conifer forests is higher than that of dry conditions. For temperate grasslands, the changes in the probability of vegetation decline from individual dry and hot conditions to compound conditions for temperate grassland are 0.02 and 0.15, respectively, implying that dry conditions have higher impacts on vegetation decline. This is consistent with previous studies showing the dominant effect of precipitation or drought on grassland productivity (Lu \textit{et al} 2021).

4. Discussion

We assessed the probabilities of vegetation decline under different climate conditions based on the meta-Gaussian model. The vegetation in arid or semi-arid regions is found to be affected by compound dry and hot extremes. For different vegetation types, temperate grasslands are particularly vulnerable to compound dry and hot conditions. Despite the difference in indicators or data products, our results are overall in agreement with findings in previous studies. The high sensitivity of ecosystems in arid and semi-arid regions to changes in droughts or high temperatures has been highlighted (Peng \textit{et al} 2013, Zhang \textit{et al} 2015, Papagiannopoulou \textit{et al} 2017, Zhao \textit{et al} 2018, Wen \textit{et al} 2019a, 2019b). For example, Liu \textit{et al} (2013) showed vegetation in semi-arid and semi-humid regions (especially temperature grassland) was more likely affected under climate extreme, especially extreme in precipitation. Based on gross primary production (GPP), Flach \textit{et al} (2021) found GPP in grasslands (and agricultural areas) generally decreased under dry and hot conditions, while forests were insensitive or even showed increased GPP values under these conditions. The proposed conditional distribution approach can also be extended to explore the impact of compound droughts and hot extremes on other sectors based on different multivariate models.

It should be noted that there are several limitations to this study. Certain uncertainties exist in data sources. Previous studies have shown that the NDVI suffers from saturation problems in high-density biomass environments (such as tropical forests) and can be sensitive to soil backgrounds (Xie \textit{et al} 2019, Wen \textit{et al} 2019a). This can result in uncertainty in vegetation dynamics based on NDVI in these regions, leading to bias in the correlation patterns and probabilistic evaluation of vegetation decline. NDVI only measures the greenness of the vegetation and only precipitation and temperature were employed to assess the relationship between vegetation and climate extremes. Thus other indicators of vegetation characteristics (e.g. net primary production) and climate variables (e.g. radiation, soil moisture, vapor pressure deficit) should also be considered in analyzing vegetation responses to compound climate extremes (Zscheischler \textit{et al} 2014, von Buttlar \textit{et al} 2018, Linscheid \textit{et al} 2020, Flach \textit{et al} 2021). In addition, we focused on the concurrent relationship between the NDVI and extreme indicators during growing seasons without consideration of the lagged effect between dry (hot) conditions. This lagged effects of ecosystems to climate extremes (several months depending on vegetation types) have been widely explored in previous studies (Wu \textit{et al} 2015, Wen \textit{et al} 2019b). For example, Wu \textit{et al} (2015) showed that the time lag of vegetation response to precipitation in arid and semi-arid areas was approximately one month and Wen \textit{et al} (2019b) found the average time lag of global terrestrial vegetation responding to the maximum temperature was around 1.68 months. Thus, defining extreme indicators at finer temporal scales (e.g. sub-seasonal scales) is needed to incorporate the lagged effect to further our understanding of vegetation response to compound extremes (Linscheid \textit{et al} 2020). Moreover, uncertainties may be associated with the oversimplified definition of growing seasons based solely on the latitude that was used in this study. These aspects will be addressed in our future studies.

5. Conclusion

In this study, we estimated the responses of global vegetation during growing seasons to different climate extremes, including dry, hot, and compound dry-hot conditions, from a probabilistic perspective. We used a meta-Gaussian model to construct a multivariate distribution of standardized indicators of the precipitation (SPI), temperature (STI), and vegetation (SNDVI) to assess the responses of vegetation to individual and compound dry and hot conditions. First, we evaluated the response of vegetation to dry conditions (SPI $\leq -1.3$), hot conditions (STI $> 1.3$), and compound dry-hot conditions (SPI $\leq -1.3$, STI $> 1.3$) in different climate regions. The probability of vegetation decline was affected by both dry and hot conditions (and their concurrences) in arid or semi-arid regions. In these regions, the average probability of vegetation decline under individual dry (hot) conditions and compound dry-hot conditions was 0.73 (0.61) and 0.78, respectively. This
indicates that the probability of vegetation decline could increase by 7% and 28% under compound dry-hot conditions compared with individual dry and hot conditions, respectively, in arid or semi-arid regions. In addition, we also evaluated the response of different vegetation types to climate conditions. Our results indicate that grassland ecosystems face a high risk of vegetation decline under compound dry and hot conditions. The results from this study provide references for understanding the impact of climate extremes on vegetation dynamics and for predicting the responses of managed and natural ecosystems under a changing climate.

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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