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1 **Negative extreme events in gross primary productivity and their drivers in China during**  
2 **the past three decades**

3  
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38  
39 **Abstract**

40  
41 Climate extremes have remarkable impacts on ecosystems and are expected to increase with

42 future global warming. However, only few studies have focused on the extreme ecological  
43 events and their drivers in China. We therefore carried out an analysis of negative extreme  
44 events in gross primary productivity (GPP) in China and the sub-regions during 1982-2015,  
45 using monthly GPP simulated by 12 process-based models (TRENDYv6) and an observation-  
46 based model (Yao-GPP). Extremes were defined as the negative 5th percentile of GPP  
47 anomalies, which were further merged into individual extreme events using a three-  
48 dimensional contiguous algorithm. Spatio-temporal patterns of negative GPP anomalies were  
49 analyzed by taking the 1000 largest extreme events into consideration. Results showed that the  
50 effects of extreme events decreased annual GPP by 2.8% (i.e. 208 TgC year<sup>-1</sup>) in TRENDY  
51 models and 2.3% (i.e. 151 TgC year<sup>-1</sup>) in Yao-GPP. Hotspots of extreme GPP deficits were  
52 mainly observed in North China (-53 gC m<sup>-2</sup> year<sup>-1</sup>) in TRENDY models and Northeast China  
53 (-42 gC m<sup>-2</sup> year<sup>-1</sup>) in Yao-GPP. For China as a whole, attribution analyses suggested that  
54 extreme low precipitation was associated with 40%-50% of extreme negative GPP events. Most  
55 events in northern and western China could be explained by meteorological droughts (i.e. low  
56 precipitation) while GPP extreme events in southern China was more associated with  
57 temperature extremes, such as cold spells in South China. The impacts of heat wave and  
58 drought are noticeable because GPP is much more sensitive to heat/drought than to cold/wet  
59 during extreme events. Combined with projected changes in climate extremes in China, GPP  
60 negative anomalies caused by drought events in northern China and by temperature extremes  
61 in southern China might be more prominent in the future.

62

63 Key words: Climate change; Extreme events; Gross primary production; Power law  
64 distribution; China

65

## 66 **1. Introduction**

67

68 Gross primary productivity (GPP) is the largest carbon flux, changes of which affect the  
69 whole terrestrial carbon cycle. The CO<sub>2</sub> fertilization and growing season extension are  
70 expected to enhance vegetation growth and increase terrestrial net primary productivity ([Los,](#)  
71 [2013](#); [Piao et al., 2013](#); [Zhu et al., 2016](#)). However, at the same time, it has been suggested that  
72 climate extremes may alter the composition, structure and function of ecosystems and therefore  
73 have potential negative impacts on terrestrial carbon uptake ([Du et al., 2018](#); [von Buttlar et al.,](#)  
74 [2018](#)). For instance, the 2003 extreme heat wave and drought in Europe caused up to 30%  
75 reduction in GPP and resulted in a strong anomalous net source of CO<sub>2</sub> ([Ciais et al., 2005](#)).  
76 Based on the commonly used definition of climate extremes, [IPCC \(2012\)](#) pointed out that  
77 changing climate has led to changes in the frequency, intensity, spatial extent, duration, and  
78 timing of weather and climate extremes, and can result in unprecedented impacts on terrestrial  
79 carbon cycle. Furthermore, climate change is projected to further increase the frequency,  
80 persistence and intensity of climate extremes in the mid- to late 21st century because of the on-  
81 going global warming ([IPCC, 2013](#); [Niu et al., 2017](#); [Sui et al., 2018](#)), which makes the impacts  
82 of future climate change on terrestrial ecosystem more uncertain ([Samaniego et al., 2018](#); [Yao](#)  
83 [et al., 2019](#)). Therefore, characterizing extreme events is an important step for the development

84 of adaptation strategies and risk reduction in the context of future climate change.

85 Extreme events are generally defined as statistically extreme or unusual episodes or  
86 occurrences, which are beyond the bounds of typical or normal variability ([Reichstein et al.,  
87 2013](#)). In scientific literature, extreme events have been defined in several ways—both from  
88 climatic and impact perspectives ([Felton and Smith, 2017](#)). [Lloyd - Hughes \(2012\)](#) firstly  
89 proposed a novel 3-dimensional (longitude, latitude, time) structure-based approach to describe  
90 drought events. [Zscheischler et al. \(2013\)](#) further improved the method and performed the first  
91 global analysis of spatio-temporally contiguous carbon-cycle extremes. This method has  
92 advantages in analyzing the size, shape, temporal evolution and other interesting quantities of  
93 extreme events. By using this technique, [Zscheischler et al. \(2014a\)](#) demonstrated that the  
94 largest 1000 negative GPP extremes accounted for a decrease in global photosynthetic carbon  
95 uptake of approximately 3.5 PgC year<sup>-1</sup>, with most events being attributable to water scarcity.  
96 [Huang et al. \(2016\)](#) quantified sensitivities of GPP to spatio-temporally contiguous  
97 hydrological extreme events and implied that vegetation in Earth System Models (ESMs) was  
98 on average more sensitive to droughts than observed. [Zscheischler et al. \(2018\)](#) pointed out  
99 that traditional assessment methods which considered only one driver at a time underestimated  
100 risk from extreme events, highlighting a better understanding of compound events. Model  
101 output of the Coupled Model Intercomparison Project Phase 5 (CMIP5) future projections  
102 suggested that negative extremes in GPP would be driven by concurrent dry and hot conditions  
103 during the 21st century ([Zscheischler et al., 2014d](#)).

104 The negative impacts of climate extremes on natural ecosystems and agriculture have been  
105 widely reported in China. [Yuan et al. \(2016\)](#) found that the 100-year return heat wave and  
106 drought in the summer of 2013 in southern China significantly reduced regional GPP, and  
107 produced the largest negative crop yield anomaly since 1960. The anomalous 2008 ice storm  
108 episode resulted in increased vegetation mortality, which exceeded recruitment for evergreen  
109 and deciduous broad-leaved species in central China ([Ge et al., 2015](#)). The most severe spring  
110 drought over the last five decades in 2010 in southwestern China reduced regional annual GPP  
111 by 4%, producing the lowest annual GPP over the period 2000–2010 ([Zhang et al., 2012](#)).  
112 Dynamic Land Ecosystem Model-based analysis showed that drought stress led to a large  
113 reduction of crop yield in China ([Ren et al., 2012](#)), with the maximum reduction in crop yield  
114 (–17.5%) occurred in 2000, a year with extreme drought and relatively high O<sub>3</sub> concentrations  
115 ([Tian et al., 2016](#)). The temperature and precipitation anomalies were the principal drivers of  
116 Normalized Difference Vegetation Index (NDVI) variation in the Yangtze River Basin (YRB)  
117 in recent years ([Cui et al., 2018](#)). These regional studies or case studies improved our  
118 understanding of the vulnerability and response of terrestrial ecosystems to individual extreme  
119 climate events. Nevertheless, most previous studies in China mainly focus on either the impacts  
120 of climate extremes ([Chen et al., 2018](#); [Yao et al., 2017](#); [Yuan et al., 2016](#)) or only a few cases  
121 of extreme ecological events ([Yuan et al., 2016](#); [Zhang et al., 2012](#)) but did not analyze a large  
122 number of extreme events in GPP in a systematic approach.

123 The sensitivity and vulnerability of ecosystem productivity to climate variability are  
124 expected to vary widely in different ecosystems and different climate zones, affected also by  
125 biodiversity or management practices ([Isbell et al., 2015](#); [Wang et al., 2017](#); [Yao et al., 2018](#)).

126 China has different climate zones that range from tropic in the south to subarctic zone in the  
 127 north, comprising wide ranges of precipitation and temperature gradients. However, there are  
 128 a limited number of studies on the effects of multiple climate drivers on GPP in China. Thus,  
 129 we intend to provide a statistical analysis of extreme events in GPP and their drivers at the  
 130 national scale and the nine sub-regions (Fig. 1a). This study aims to (1) diagnose the spatial  
 131 and temporal patterns of extreme events in GPP in China; (2) attribute these extreme events to  
 132 climatic drivers; (3) explore size distribution of extreme ecological events for different climate  
 133 drivers and different regions. We expect to provide a better understanding of the characteristics  
 134 of extreme events and their responses to different drivers.

135

## 136 2. Materials and methods

137

### 138 2.1. GPP data sources

139

140 **Table 1**

141 Summary of monthly GPP estimates, climate and fire data used in this study. Some of the  
 142 datasets extend beyond 1982–2015, but the analysis in this paper is confined to those years.

143

Dataset	Variable	Resolution	Period	Citation
Yao-GPP	GPP	0.1°	1982-2015	( <a href="#">Yao et al., 2018</a> )
Historical climate carbon cycle intercomparison project (TRENDYv6)	GPP and soil moisture	0.5°-1°	1982-2015	( <a href="#">Le Quéré et al., 2018</a> )
Institute of Tibetan Plateau Research, Chinese Academy of Sciences (ITPCAS)	Air temperature and precipitation	0.1°	1982-2015	( <a href="#">Chen et al., 2011</a> )
Climatic Research Unit (CRU)	Air temperature and precipitation	0.5°	1982-2015	( <a href="#">Harris et al., 2014</a> )
Climatic Research Unit (CRU)	self-calibrating Palmer Drought Severity Index	0.5°	1982-2015	( <a href="#">van der Schrier et al., 2013</a> )
Global Fire Emissions Database, Version 4 (GFEDv4)	Burned area and fire emissions	0.25°	1997-2015	( <a href="#">Randerson et al., 2017</a> )

144

145 Results from an observation-based model of GPP (Yao-GPP, hereafter and [Table 1](#)), with  
 146 0.1° spatial resolution and monthly temporal frequency over China, were obtained from [Yao et al. \(2018\)](#). This GPP data is developed using a machine learning technique, model tree ensembles (MTE) ([Jung et al., 2011](#)) with eddy flux measurements from 40 sites in China and  
 147  
 148

149 the surrounding countries. The high-resolution GPP data can successfully capture the spatio-  
150 temporal variations of the GPP observed at the flux sites, including validation flux sites that  
151 were not part of the MTE training set (Yao et al., 2018).

152 Besides the above observation-based model, we also used monthly GPP from process-  
153 based ecosystem models that took part in the historical climate carbon cycle model  
154 intercomparison project (TRENDYv6, Table A.1). The model simulations all followed the  
155 same experimental protocol (Le Quéré et al., 2018; Sitch et al., 2015) and were driven with the  
156 same climate data from the Climatic Research Unit and National Center for Environmental  
157 Prediction (CRU-NCEP) climate forcing reconstruction. The GPP outputs were from the S3  
158 TRENDY simulations which used observed CO<sub>2</sub> concentrations, changing climate, and land  
159 cover changes as forcing over the period 1860–2016. Many different process-based models  
160 were used in TRENDY simulations. As coarse spatial resolution makes it not possible to  
161 diagnose enough GPP extreme events, model simulations with coarser resolution than 1° were  
162 excluded. Consequently, 12 models were finally selected: CABLE (Haverd et al., 2017),  
163 CLM4.5 (Oleson et al., 2013), DLEM (Tian et al., 2015), ISAM (Jain et al., 2013), LPJ-GUESS  
164 (Smith et al., 2014), LPJ-wsl (Sitch et al., 2003), LPX-Bern (Keller et al., 2017), ORCHIDEE  
165 (Krinner et al., 2005), ORCHIDEE-MICT (Guimberteau et al., 2018), SDGVM (Woodward et  
166 al., 1995), VEGAS (Zeng et al., 2005) and VISIT (Kato et al., 2013), and see references and  
167 further model details contained in Le Quéré et al. (2018).

168

## 169 2.2. Climatic data

170 To attribute negative extreme events in GPP to drivers, we used air temperature (Ta),  
171 precipitation (P), soil moisture (SM), self-calibrating Palmer Drought Severity Index (scPDSI)  
172 (van der Schrier et al., 2013), burned area (BA) and CO<sub>2</sub> emissions from fires (FE) (Table 1).  
173 Gridded Ta and P data (0.5° spatial resolution) was taken from the monthly dataset compiled  
174 by the CRU of the University of East Anglia, UK. This CRU datasets span the period 1901-  
175 2015 and can be obtained at <http://www.cru.uea.ac.uk/data>. As Yao-GPP was driven by another  
176 forcing dataset, which was developed by Data Assimilation and Modeling Center for Tibetan  
177 Multi-spheres, Institute of Tibetan Plateau Research, Chinese Academy of Sciences (ITPCAS,  
178 <http://westdc.westgis.ac.cn>), the corresponding monthly Ta and P (Fig. A.1) were used to  
179 identify the driving factors for Yao-GPP. We used the respective SM data from TRENDY  
180 models to diagnose the contribution of SM to their GPP extremes. As for Yao-GPP, averaged  
181 TRENDY SM was used in attribution analysis. The scPDSI data, which represents an index for  
182 comparing the relative spatio-temporal variability of soil moisture changes over wide regions,  
183 was also collected from CRU. The Global Fire Emissions Database, Version 4 (GFEDv4)  
184 provides global estimates of monthly burned area and carbon emissions from fire  
185 ([https://daac.ornl.gov/VEGETATION/guides/fire\\_emissions\\_v4.html](https://daac.ornl.gov/VEGETATION/guides/fire_emissions_v4.html)). This data has a 0.25°  
186 spatial resolution and is available from July 1997 through 2015.

187

## 188 2.3. Preprocessing method

189 All of the gridded datasets were first resampled to 0.1° × 0.1° spatial resolution using the  
190 nearest neighbor interpolation. The original GPP and climate variables contain long-term

191 trends and strong seasonal cycles. For these variables (i.e. Ta, P, scPDSI, SM and all the GPP  
192 data), the temporal linear trend and mean seasonal cycle were removed in each grid cell to get  
193 the anomalies of the time series data. For the variables describing episodic events (BA and FE),  
194 we divided them by the total sum of the respective time series in each grid cell. The  
195 preprocessing produced anomalies in de-trended GPP and climate, which represents deviations  
196 from the mean behavior ([Zscheischler et al., 2013](#)).

197

#### 198 2.4. Negative extreme events detection

199 In scientific literature, extremes are usually defined based on either the probability of  
200 occurrence of given quantities or threshold exceedances ([IPCC, 2012](#)). In order to quantify the  
201 extreme ecological events, we defined extremes as the negative 5th percentile of all the GPP  
202 anomalies (derived from the above-mentioned preprocessing). Contiguous extreme negative  
203 GPP anomalies (i.e. voxels) are further merged into individual extreme events following  
204 [Zscheischler et al. \(2014a\)](#). By “contiguous”, we mean any of the 26 neighbors in three-  
205 dimensional (latitude × longitude × time) space also experiencing an extreme GPP anomaly.  
206 The size of an extreme event is the summation of GPP anomalies over the spatio-temporal  
207 domain of the event cluster. With this algorithm, each GPP datasets produced 1000~5000  
208 extreme events for the whole China during the study period. As we are more interested in large  
209 events and hope to compare between models, we investigated the 1000 largest negative extreme  
210 events in GPP ( $GPP_{1000}$ ) for the whole China and the 100 largest extreme events for each of the  
211 nine sub-regions.

212

#### 213 2.5 Power laws identification

214 Power laws in frequency or size distributions were previously detected in a variety of  
215 natural phenomena ([Clauset et al., 2009](#)), such as global fire size distributions ([Hantson et al.,  
216 2015](#)) as well as intensities of earthquakes. In this study, we want to analyze the size  
217 distribution of extreme ecological events for different climate drivers and different regions in  
218 China. According to [Zscheischler et al. \(2013\)](#), the size distribution of extreme events ( $s_e$ ) can  
219 also be well approximated by a power law relationship as follows:

220

$$221 \quad p(s_e) \sim s_e^{-\alpha} \quad (1)$$

222

223 where  $\alpha$  is a constant parameter of the distribution known as the exponent or scaling parameter.  
224 The exponent  $\alpha$  of the size distribution was diagnosed using the fitting technique of maximum  
225 likelihood presented by [Clauset et al. \(2009\)](#). This algorithm has been widely applied in  
226 diagnosing power law distributions in empirical data ([Scannell et al., 2016](#)). The  $\alpha$ -value from  
227 the power-law function provides information on asymmetry in the size distribution of extreme  
228 events, indicating the relative number of extreme events of different sizes. An increase in  $\alpha$   
229 suggests an increasing proportion of small extreme events relative to large ones. It can also be  
230 used as an index to investigate the different patterns in extreme events for different drivers and  
231 regions. Clauset’s method provides a goodness-of-fit parameter p-value, where p-value > 0.1  
232 indicates a good fit.

233

## 234 2.6. Attribution of negative extreme events

235 In order to identify possible drivers of individual negative extreme events in GPP, we  
236 adopted the attribution method from [Zscheischler et al. \(2013\)](#). For each event, we calculate  
237 the median of driver variable anomalies over the spatio-temporal domain of the event, which  
238 directly represents the anomaly intensity of the corresponding driver during the event. Then,  
239 we let the event shift in each time step and obtain a series of medians ( $M_s$ ) as a function of time.  
240 As there are possibly lagged responses of ecosystems to all these drivers ([Reichstein et al.,  
241 2013](#)), we consider time lags of a maximum of three months. Then, if any of the medians within  
242 three months preceding the events is less (higher) than the 10th (90th) percentile of  $M_s$ , the  
243 driver (e.g. a cold spell or heat wave) is selected as influential for that event. An GPP extreme  
244 event is attributed to fire if either BA or CO<sub>2</sub> emissions from fires during the event is higher  
245 than 90th percentile. A single event is possible to be explained by multiple drivers. The  
246 attribution rate is defined as the proportion of studied events, which are attributed to any of the  
247 nine drivers (i.e. for all drivers) or a typical driver (e.g. for cold spell).

248

## 249 2.7 GPP sensitivity during the extreme events

250 We explored GPP sensitivity of different models to precipitation or temperature anomalies  
251 (i.e. heat wave, cold spell, drought and wet). For each model, the single driver induced extreme  
252 GPP events were selected in order to extract the impact of this driver from potential additive  
253 effect. And then, we divided the mean GPP anomalies by mean precipitation or temperature  
254 anomalies over the voxels in selected extreme events. For example, the GPP sensitivity to  
255 drought is expressed as:

$$256 \quad Sens_{-p} = \frac{|\overline{GPP}_{an,-P}|}{|\overline{P}_{an,-P}|} \quad (2)$$

257 where  $\overline{GPP}_{an,-P}$  is averaged GPP anomalies over all voxels from exclusively drought (i.e.  
258 low P) induced extreme events among the studied 1000 events;  $\overline{P}_{an,-P}$  is averaged  
259 precipitation anomalies over the same voxels. Thus,  $Sens_{-p}$  is the sensitivity of modelled GPP  
260 to the driver, that is GPP deficit for each precipitation anomaly during extreme events.

261

## 262 3. Results

263

### 264 3.1. Spatio-temporal patterns of extreme events

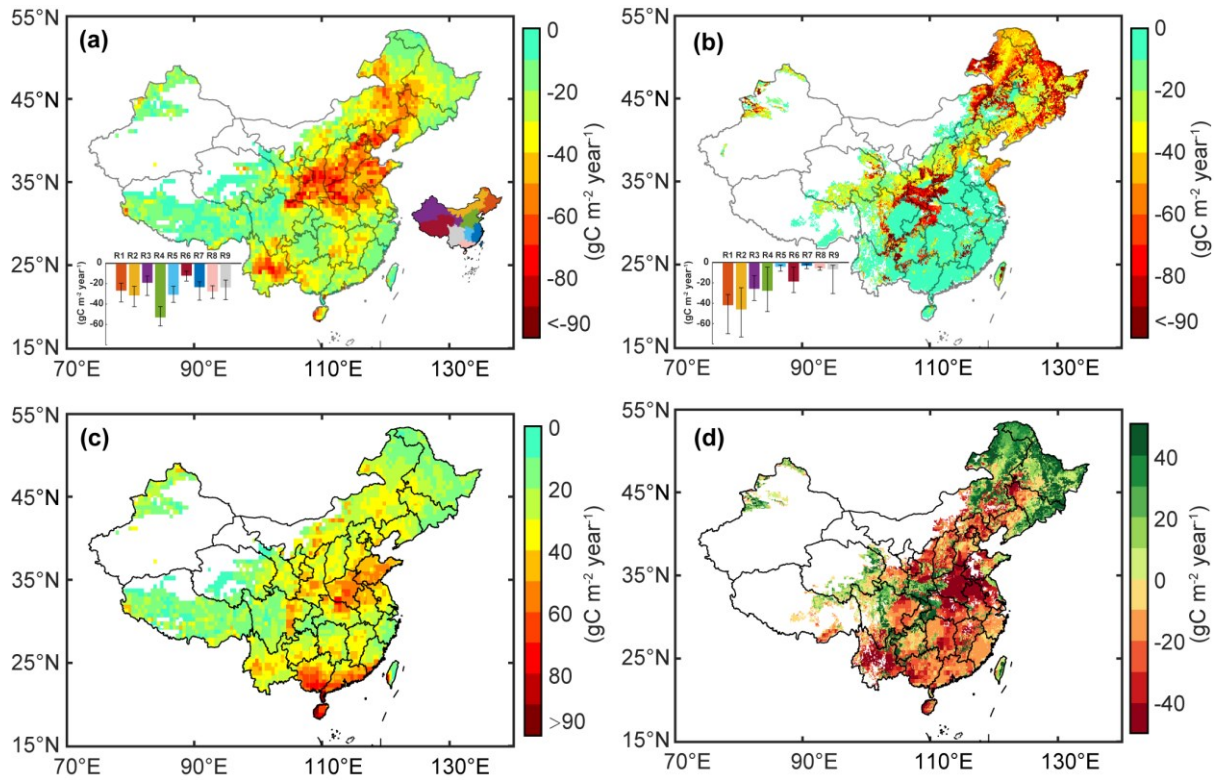
265 Most (95%) of the GPP<sub>1000</sub> had a duration of 1-7 months ([Fig. A.2](#)). To map spatial  
266 distribution of GPP anomalies, the GPP<sub>1000</sub> over China were aggregated in time. In details, for  
267 a specific location, all anomalies in GPP classed as extreme events were summed and then  
268 divided by 34 years. TRENDY multi-model median showed hotspots of extreme events in  
269 North China where the GPP extreme anomalies could reach up to -70 gC m<sup>-2</sup> year<sup>-1</sup> ([Fig. 1a](#)).  
270 In addition, regional medians of North China, Inner Mongolia and Central China had prominent  
271 GPP extreme anomalies of -53, -31 and -30 gC m<sup>-2</sup> year<sup>-1</sup>, respectively. In contrast, both  
272 Northwest China and Qinghai-Tibetan Plateau (QTP) were less impacted by extreme events  
273 with regional median GPP anomalies of approximately -10 gC m<sup>-2</sup> year<sup>-1</sup>.



274 According to the Yao-GPP data-driven model, the anomalies became larger in magnitude  
275 from southeast to northwest (Fig. 1b). The lowest impacts were diagnosed with GPP deficits  
276 of less than  $-10 \text{ gC m}^{-2} \text{ year}^{-1}$  in Southwest China and Sichuan Basin where there are relatively  
277 lower altitudes. The largest negative GPP extreme events were diagnosed in Inner Mongolia ( $-$   
278  $46 \text{ gC m}^{-2} \text{ year}^{-1}$ ), Northeast China ( $-42 \text{ gC m}^{-2} \text{ year}^{-1}$ ) and North China ( $-28 \text{ gC m}^{-2} \text{ year}^{-1}$ )  
279 in Yao-GPP. The prominent extreme events were generally diagnosed in mountainous regions  
280 such as Qinling Mountains in North China around Sichuan Basin, and Greater Khingan  
281 Mountains and Changbai Mountains in Northeast China. Although these regions had less GPP  
282 than South China, much more significant GPP deficits were detected. Hot spots of extreme  
283 events were detected in Northeast China for Yao-GPP but in North China for the process-based  
284 ecosystem models. Compared with Yao-GPP, the process-based ecosystem models  
285 overestimate the magnitude of extreme events in Northeast China and underestimate in North  
286 China (Fig. 1d). Disagreement between the process-based ecosystem models was mainly found  
287 in North China and South China (Fig. 1c).

288 The  $\text{GPP}_{1000}$  were aggregated in space to produce the monthly evolution of GPP anomalies  
289 in China, which was further aggregated to show seasonal differences (Fig. 2). The median over  
290 the TRENDY models indicated that extreme events in summer produced the most GPP negative  
291 anomalies by  $-30.4 \text{ TgC mon}^{-1}$ , which accounted for 45% anomalies of the year, followed by  
292 spring, autumn and winter. Boxplot exhibited that LPX-Bern was an outlier in summer and  
293 autumn while VISIT was an outlier in winter over the 12 process-based models because of their  
294 overestimates of GPP deficits. The GPP deficits in Yao-GPP were smaller than the TRENDY  
295 median in spring, autumn and winter but slightly larger in summer, which consequently made  
296 the summer accounting for 68% of the mean annual anomalies in Yao-GPP. Among the 12  
297 TRENDY models, LPX-Bern produced the largest extreme events by  $-475.2 \text{ TgC year}^{-1}$  while  
298 DLEM produced the smallest extreme events by  $-98.4 \text{ TgC year}^{-1}$  for the  $\text{GPP}_{1000}$  in China (Fig.  
299 A.3). The TRENDY median and Yao-GPP estimated values of  $-207.6 \text{ TgC year}^{-1}$  and  $-151.2$   
300  $\text{TgC year}^{-1}$  for the sum of the  $\text{GPP}_{1000}$ , accounting for 2.8% and 2.3% of mean annual GPP,  
301 respectively.

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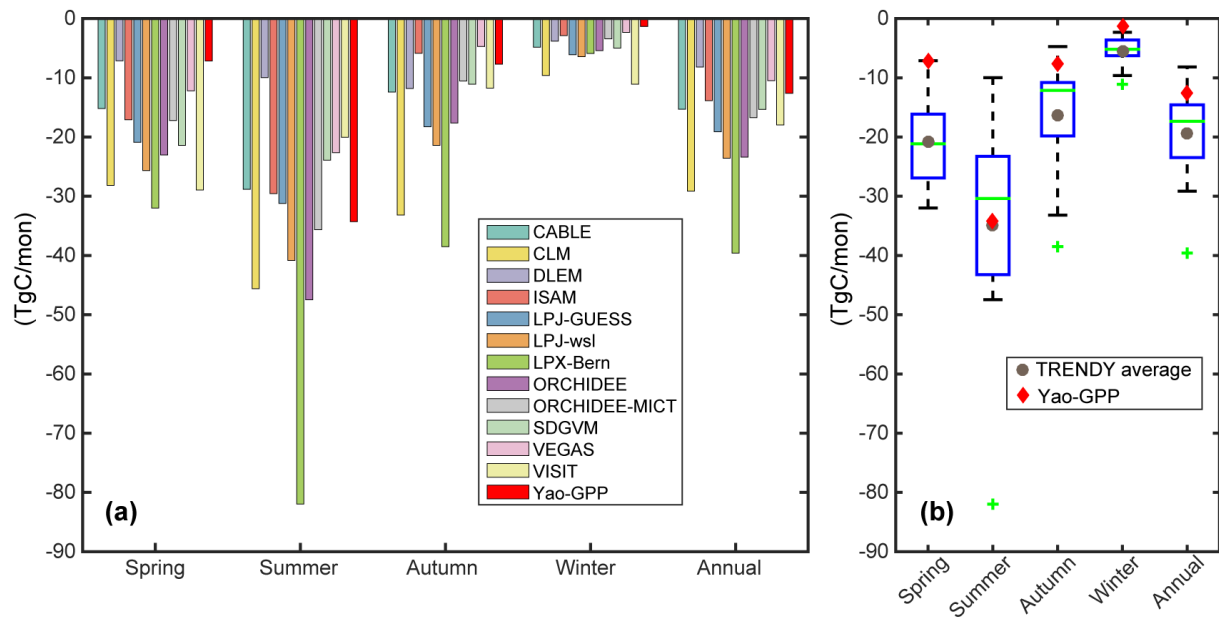
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**Fig. 1.** Spatial distributions of (a) the magnitude of the 1000 largest negative extreme events in GPP ( $\text{GPP}_{1000}$ ) during 1982-2015 from the median of the 12 process-based TRENDY models and (b) the observation-based GPP model Yao-GPP, (c) standard deviation over TRENDY models and (d) the TRENDY median minus Yao-GPP (i.e. panel (a) minus panel (b)). The left insets in panel (a) and (b) denote the median (i.e. bar graph), 25th and 75th percentile (i.e. error bar) of GPP anomalies for each sub-region. The right inset in panel (a) presents the definition of the nine sub-regions in China. R1 (red): Northeast China; R2 (orange): Inner Mongolia; R3 (purple): Northwest China; R4 (green): North China; R5 (sky blue): Central China; R6 (dark red): Qinghai-Tibetan Plateau (QTP); R7 (dark blue): Southeast China; R8 (pink): South China, and R9 (grey): Southwest China.



315

316 **Fig. 2.** (a) Bar graph and (b) boxplot of GPP extremes in four seasons and annual mean. The  
 317 legend in panel (a) distinguishes the 13 GPP datasets. The red diamonds and gray dots in panel  
 318 (b) represent Yao-GPP and averages over the 12 process-based models, respectively. The lower  
 319 and upper edges of the box indicate 25th and 75th percentile of the GPP anomalies over the 12  
 320 process-based models. The green line and cross are median and outliers, respectively. Note that  
 321  $1 \text{ TgC} = 10^{12} \text{ gC}$ .

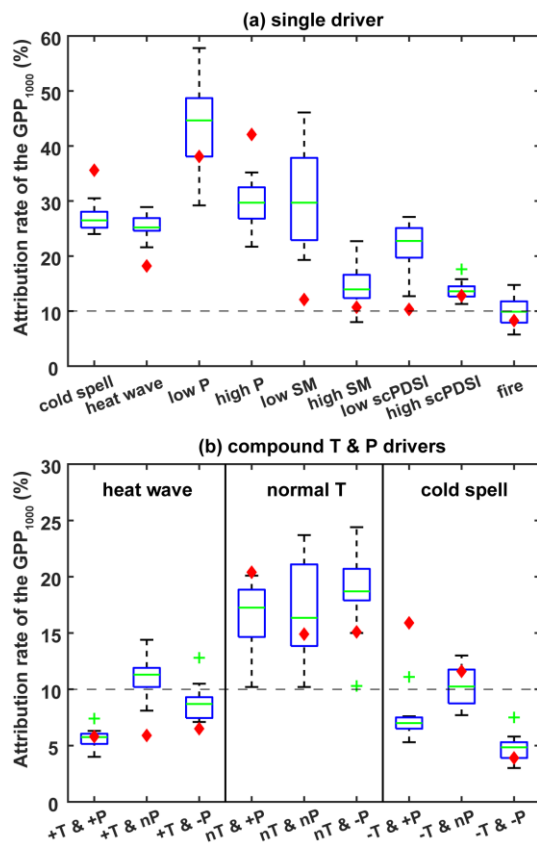
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### 323 3.2. Attribution of negative GPP extremes in China and the nine sub-regions

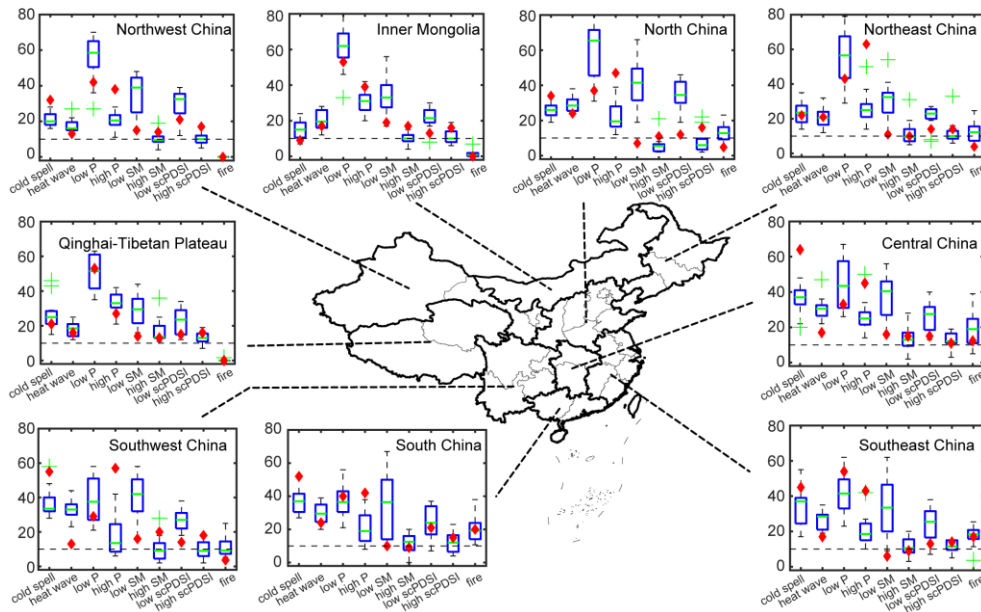
324 The eight climate indices and fire variables were regarded as potential drivers of the  
 325  $\text{GPP}_{1000}$  in China. As for single climate drivers, we investigated both positive and negative  
 326 anomalies in  $T_a$ ,  $P$ ,  $SM$  and  $scPDSI$  (Fig. 3a). According to the multi-model median, both cold  
 327 spell and heat wave were influential for  $\sim 26\%$  of the extreme events. Meteorological droughts  
 328 (i.e. low  $P$ ) were associated with  $\sim 58\%$  of the extreme events, making it the major driver among  
 329 the nine indices. In addition, extreme events were more related to droughts than floods as low  
 330  $P$ , low  $scPDSI$  and low  $SM$  accounted for much more events than the corresponding positive  
 331 values of those indices (i.e. high  $P$ , high  $scPDSI$  and high  $SM$ ). But in the arguably more  
 332 realistic Yao-GPP dataset, cold spell explained 36% of the extreme events, which was much  
 333 larger than heat wave (18%). Drought indices were associated less extreme negative events  
 334 than wet indices, which was different from the TRENDY model results. The 10% significance  
 335 threshold denotes that  $\text{GPP}_{1000}$  in Yao-GPP were nearly independent of  $SM$ ,  $scPDSI$  and fire  
 336 indices. As GPP extreme events are mainly driven by  $T_a$  and  $P$  anomalies in China at national  
 337 scale, we explored the possible compound T&P effects (Fig. 3b). The  $\text{GPP}_{1000}$  from TRENDY  
 338 models and Yao-GPP were significantly associated with  $P$  anomalies (both wet and drought)  
 339 during normal  $T_a$  condition. No significant compound T&P effects were observed for  
 340 TRENDY models and only significant compound cold and wet conditions were linked to GPP  
 341 extreme events in Yao-GPP.

342 China has different climate zones so that the response of GPP extreme events to driver

343 indices are expected to be different across those zones. As shown in Fig. 4, the TRENDY  
 344 median indicated that extreme events in most sub-regions were mostly associated with low P,  
 345 especially for North China (66%) and Inner Mongolia (62%), but not in South China (37%).  
 346 In contrast, temperature extremes (i.e. cold spell or heat wave) explained more extreme events  
 347 in southern China (60%-70%) than in northern China (30%-50%). For comparison with the  
 348 different response to low P, the impacts of soil drought (i.e. low SM and low scPDSI) were  
 349 rather stable and explained 35%-40% and 25%-30% among all sub-regions in China. In  
 350 particular, low SM was associated with 42% of extreme events, followed by low P (38%) and  
 351 cold spell (34%) in Southeast China. This suggested a decoupling between P and SM in  
 352 controlling GPP extremes, with P anomalies combined with Ta anomalies enhancing  
 353 evapotranspiration and decreasing SM in southern China to cause GPP extremes being more  
 354 influenced by SM than by just P. The Yao-GPP also presented the different vulnerability of  
 355 extreme events in GPP to temperature extremes between northern and southern China.  
 356 Compared with Yao-GPP, the TRENDY models largely underestimated attribution rate for high  
 357 P in most sub-regions but overestimated attribution rate for low P in northern China. For the  
 358 period of 1997-2015, both Yao-GPP and TRENDY median indicated that fire was linked to 20%  
 359 of large events in South China and Southeast China. In terms of compound T&P effects (Fig.  
 360 A.5), we found the GPP<sub>100</sub> from TRENDY were significantly associated with concurrent heat  
 361 and drought events in Northwest China, Inner Mongolia, North China, Central China and  
 362 Southeast China. But in Yao-GPP, GPP<sub>100</sub> in most sub-regions of China were linked to  
 363 compound cold and wet events.  
 364



366 **Fig. 3.** Attribution rate of the  $GPP_{1000}$  for single or compound drivers. Boxplots result from the  
 367 TRENDY models and red diamonds are for Yao-GPP. The horizontal dashed lines denote the  
 368 significance threshold (10%), below which the driver and GPP variation are expected to be  
 369 independent. The nT and nP in panel (b) represent normal Ta (i.e. not extreme Ta condition)  
 370 and normal P, respectively. The attribution of the  $GPP_{1000}$  in China for each model is shown in  
 371 Fig. A.4.  
 372



373  
 374 **Fig. 4.** Attributions rate (%) of GPP extreme events to climate drivers and fire in the nine sub-  
 375 regions of China. The largest 100 negative extreme events ( $GPP_{100}$ ) were used for each sub-  
 376 region.

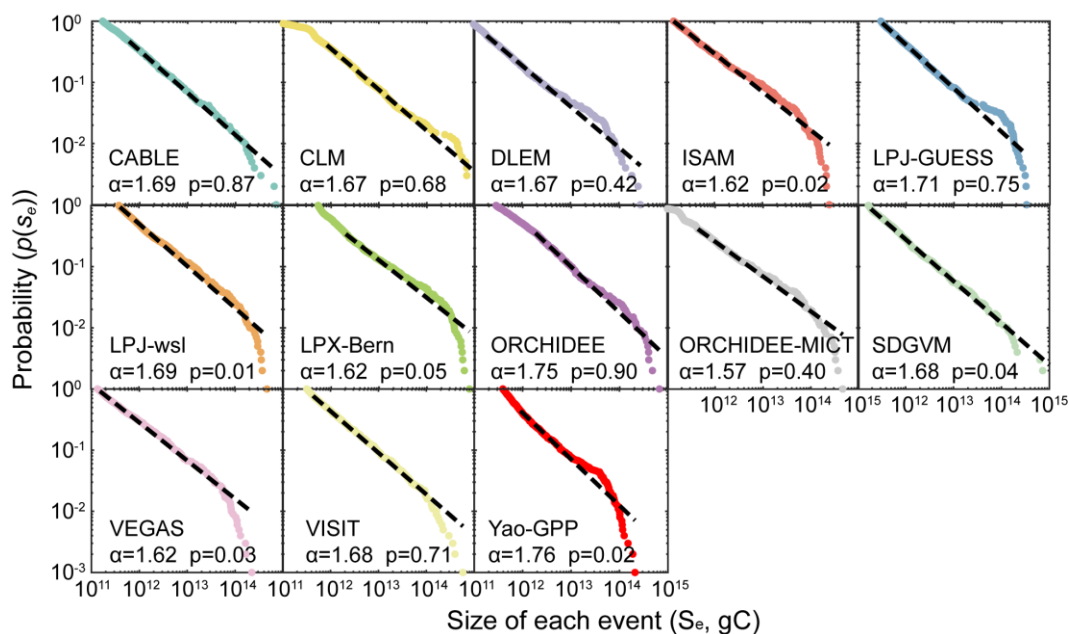
377  
 378 3.3. Size distribution of GPP extreme events

379 In order to understand the characteristic of extreme events, it is crucial to know the size  
 380 distribution of extreme events. The sizes of the  $GPP_{1000}$  from the 13 GPP datasets were well  
 381 fitted by power law distributions (Fig. 5). The power law exponent ( $\alpha$ -value) agreed well  
 382 among the 13 datasets, ranging from 1.57 to 1.76, with the highest value in Yao-GPP and the  
 383 lowest value in ORCHIDEE-MICT. The median  $\alpha$ -value ( $\alpha_m$ -value) over the TRENDY models  
 384 was 1.68, which is slightly smaller than  $\alpha$ -value in Yao-GPP ( $\alpha_Y$ -value = 1.76).

385 It was found that different climate regions and vegetation types resulted in different  $\alpha$ -  
 386 value of fire size distribution (Hantson et al., 2015). Therefore, we supposed that size  
 387 distribution of extreme events could have variations for different drivers and in sub-regions.  
 388 As for the TRENDY models, the  $\alpha_m$  had substantial fluctuation between 1.52-2.18 for different  
 389 drivers (Fig. 6). The smallest  $\alpha_m$ -value was observed for low SM (1.53, the range of 1.47-1.76  
 390 in TRENDY models) and low scPDSI (1.52, the range of 1.40-1.68 in TRENDY models)  
 391 related extreme events and the largest  $\alpha_m$ -value (2.18, the range of 2.06-3.05 in TRENDY  
 392 models) was diagnosed for fire related extreme events (Table A.2). It means that low SM tended  
 393 to result in large GPP negative anomalies respective to small events while fire was more

394 associated to small sized extreme events in China. Furthermore, all  $\alpha_m$ -values for drought  
 395 induced extreme events, including meteorological drought (i.e. low P) and soil drought (i.e.  
 396 low SM and low scPDSI), were significantly smaller than wet related events. Similarly, the  
 397 Yao-GPP also showed that low SM (2.09) and low scPDSI (2.18) were correspondingly smaller  
 398 than high SM (2.18) and high scPDSI (2.22) related events, suggesting more vulnerability of  
 399 GPP to drought events than extreme wet events. Compared with  $\alpha_Y$ -values,  $\alpha_m$ -values were  
 400 overall underestimated. Similarly, the  $\alpha$ -values for the GPP<sub>100</sub> for each sub-region in China  
 401 were also diagnosed (Fig. A.6). Clear spatial decreasing gradients in  $\alpha_m$ -values were found  
 402 from the northwest to the southeast, indicating relatively more large-events were diagnosed in  
 403 Southeast China (1.65) and North China (1.65).

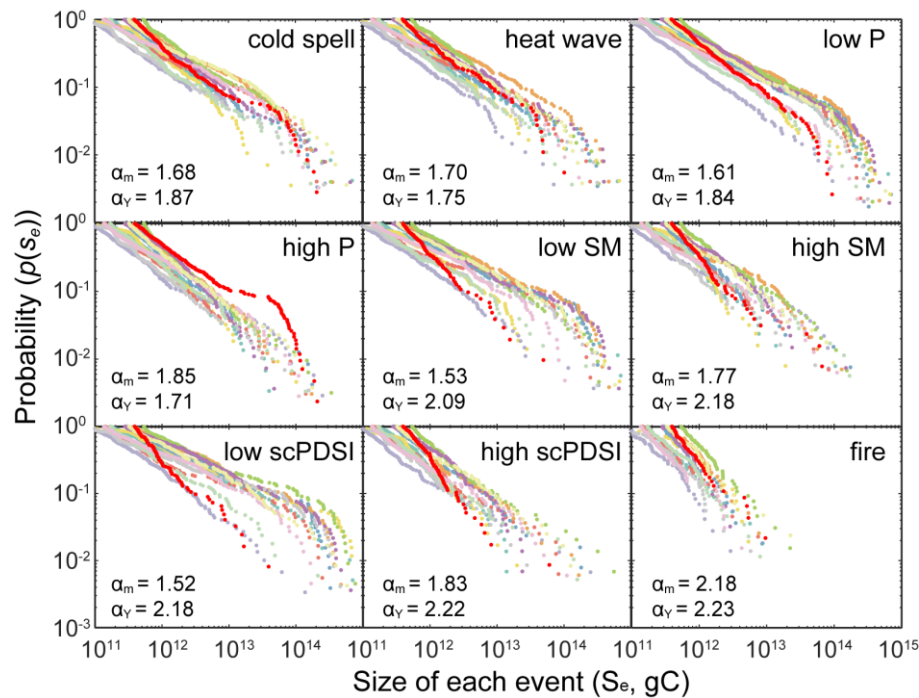
404



405

406 **Fig. 5.** Fitted power law distributions to sizes of negative GPP anomalies (gC) for the 13 GPP  
 407 datasets. The letter  $\alpha$  denotes the exponent of the fitted power law. Colored dots are the GPP<sub>1000</sub>  
 408 for each dataset and black dashed lines are fitted power law distribution. A p-value > 0.1  
 409 indicates a good fit.

410



411

412 **Fig. 6.** Probability distributions of sizes of extreme events caused by the nine drivers,  
 413 respectively. The color legend to distinguish GPP datasets is the same as Fig. 2. The letter  $\alpha_m$   
 414 and  $\alpha_Y$  are median of the fitted exponents over the TRENDY models and exponent for Yao-  
 415 GPP, respectively. The sample size, power law fitting and goodness-of-fit parameters are  
 416 presented in Table A.2.

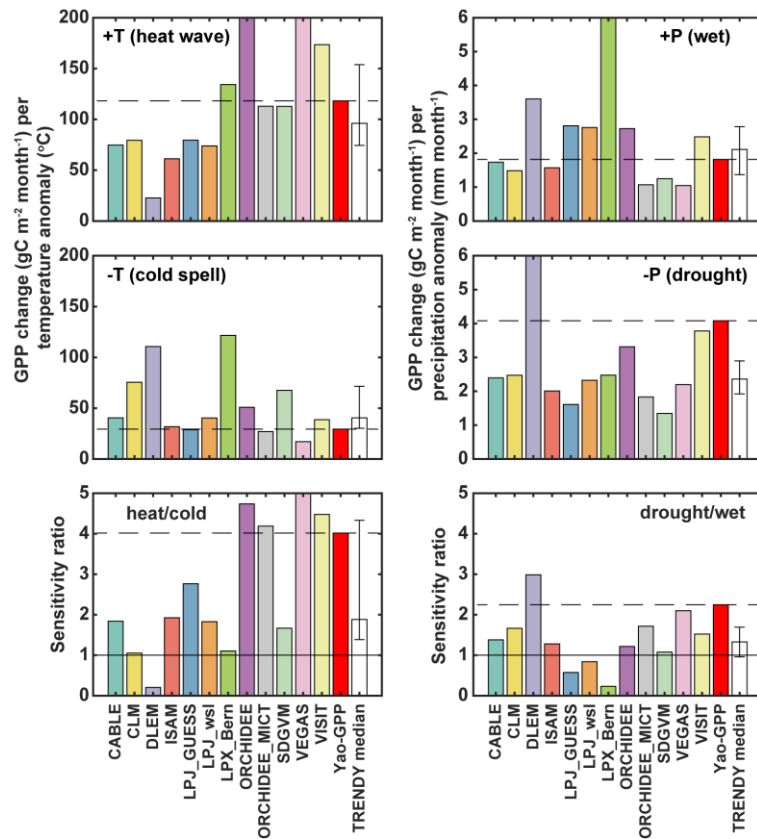
417

### 418 3.4 GPP sensitivity to temperature and precipitation anomalies

419 The impacts (anomalies) of the extreme events is also determined by models' sensitivity.  
 420 Thus, we explored the GPP sensitivities of the models to evaluate the model performance  
 421 during extreme events (Fig. 7). The GPP sensitivities of Yao-GPP to heat, cold, wet and drought  
 422 were  $118 \text{ gC m}^{-2} \text{ month}^{-1} \text{ }^\circ\text{C}^{-1}$ ,  $29 \text{ gC m}^{-2} \text{ month}^{-1} \text{ }^\circ\text{C}^{-1}$ ,  $1.8 \text{ gC m}^{-2} \text{ mm}^{-1}$  and  $4.1 \text{ gC m}^{-2} \text{ mm}^{-1}$ ,  
 423 respectively. Compared with Yao-GPP, the TRENDY median underestimated the sensitivities  
 424 to heat (-18%) and drought (-42%) but overestimated the sensitivities to cold (37%) and wet  
 425 (16%). Nevertheless, both TRENDY median and Yao-GPP demonstrated significantly higher  
 426 GPP sensitivities to heat and drought than to cold and wet (i.e. heat/cold > 1, drought/wet > 1),  
 427 highlighting the negative impacts of heat and drought events.

428 The GPP sensitivity to temperature or precipitation anomalies (i.e. heat, cold, wet and  
 429 drought) vary significantly across the 13 models. For example, ORCHIDEE-MICT showed the  
 430 same GPP sensitivities to heat, cold as well as heat/cold ratio as Yao-GPP, but presented less  
 431 response to precipitation extremes. In fact, all the process-based models except DLEM showed  
 432 less sensitive to drought than Yao-GPP. 12 out of the 13 models was more sensitive to heat than  
 433 to cold events and 10 out of the 13 models was more sensitive to drought than to wet events.  
 434 TRENDY models had remarkable disagreement in heat/cold sensitivity ratio but showed better  
 435 agreement in drought/wet sensitivity ratio.

436



437

438 **Fig. 7.** Sensitivities of GPP anomalies to single driver of heat wave, cold spell, wet and drought  
 439 during extreme events among the 13 models. The white bar in each panel shows TRENDT  
 440 median, 25th and 75th percentile. The horizontal dashed line denotes Yao-GPP value.

441

#### 442 4. Discussion

443 The characterization of extreme events in vegetation productivity is critical for  
 444 understanding its role in regulating regional carbon cycles and its climatic drivers. As far as we  
 445 know, this might be the first attempt to analyze spatio-temporally contiguous extreme GPP  
 446 events at the national scale and sub-regions in China. Spatial distribution of negative extreme  
 447 events from Yao-GPP exhibited hotspots in Northeast China and Qinling Mountains where  
 448 high interannual variability was also diagnosed in [Yao et al. \(2018\)](#). [Xu et al. \(2012\)](#) also found  
 449 that the area experiencing negative vegetation growth anomalies increased in northern China  
 450 but decreased in southern China during 2000s, although the whole China experienced an  
 451 increasing trend in heat waves and drought events. A strong negative NPP trend was diagnosed  
 452 in Northeast China ([Sitch et al., 2015](#)), further emphasizing more concerns should be given to  
 453 northern China. Based on four global GPP datasets, [Zscheischler et al. \(2014a\)](#) demonstrated  
 454 that a few extreme events dominated global interannual variability in GPP. It could explain the  
 455 similar spatial distribution between GPP negative extremes and interannual variability of GPP  
 456 in most regions in China. This result highlights the importance of extreme events in regulating  
 457 regional carbon cycles. In general, the effects of extreme events decreased annual GPP by 2.8%  
 458 and 2.3% in TRENDY model and Yao-GPP, respectively. TRENDY median and Yao-GPP  
 459 showed that extreme events in summer contributed to 45% and 68% of GPP negative anomalies,



460 respectively, followed by spring, autumn and winter. This may be because summer usually  
461 corresponds to the highest GPP, and thus the highest absolute GPP anomalies are likely to occur  
462 when extreme events happen in summertime. For instance, in the summer of 2013, the strongest  
463 drought and heat wave on record for the past 113 years resulted in a 39–53% reduction of the  
464 annual net carbon sink of China's terrestrial ecosystems ([Yuan et al., 2016](#)).

465 The attribution analyses implied that low P explained 58% and 38% of the  $GPP_{1000}$  in  
466 TRENDY models and Yao-GPP, respectively. In global drought-affected areas, the reduced  
467 carbon uptake could explain larger than 70% of the interannual variation in GPP ([Du et al.,  
468 2018](#)), also emphasizing the overall significantly negative impacts of meteorological droughts  
469 on vegetation productivity. Nevertheless, the vulnerability of GPP to these nine drivers showed  
470 marked difference between northern and southern China. A few mechanisms may explain the  
471 phenomenon that droughts were associated with much more extreme events in northern China  
472 (~60%) than in southern China (~40%) in TRENDY models. Firstly, the different climate is  
473 partly responsible for this different response that northern China experiences annual  
474 precipitation with less than 800 mm year<sup>-1</sup> while southern China is moister ([Fig. A.1](#)). In  
475 addition, consecutive dry days averaged over 1961–2015 for northern China is larger than 50  
476 days year<sup>-1</sup>, which is much higher than southern China ([Shi et al., 2018](#)). Secondly, southern  
477 China has much higher tree density ([Crowther et al., 2015](#)), while most regions of northern  
478 China (e.g. Inner Mongolia and Northwest China) are mainly dominated by grasslands ([Yao et  
479 al., 2018](#)). Grasslands are more susceptible to droughts in contrast to forests ([Reichstein et al.,  
480 2013](#)), probably because of shallower root system in grasslands ([Teuling et al., 2010](#)). However,  
481 compared with Yao-GPP, TRENDY models seem to overestimate the attribution rate to  
482 droughts (i.e. low P, low SM and low scPDSI) but underestimate the sensitivity to low P. The  
483 over-response of GPP and leaf area index in Earth system models to droughts has previously  
484 been suggested by [Huang et al. \(2016\)](#). Both types of GPP datasets demonstrated that  
485 vegetation in South China is mostly vulnerable to temperature extremes, in particular cold  
486 spells. This result is consistent with results from [Xu et al. \(2016\)](#) and [Yao et al. \(2018\)](#) that the  
487 sensitivity to temperature variability is higher in southern China, especially for forests.  
488 Compared with Yao-GPP, TRENDY models systematically underestimated cold spell-induced  
489 events and overestimated heat wave-induced events in southern China. A better representation  
490 of photosynthetic temperature acclimation in process-based models is critical to reduce the  
491 uncertainty in modeling the carbon cycle-climate feedback ([Lombardozi et al., 2015](#)).  
492 [Zscheischler et al. \(2014d\)](#) highlighted the strong compound hot and dry events during 21st  
493 century based on CMIP5 future projections. We also found the significant impacts of  
494 concurrent hot and dry events in most sub-regions of China but the  $GPP_{1000}$  were mostly  
495 associated with P anomalies during normal Ta for China as a whole.

496 The power law exponent of size distributions of extreme events in China is 1.68 in  
497 TRENDY median and 1.76 in Yao-GPP, which are consistent with that in Asia (1.61) and  
498 different continental range (1.55–1.75) as extracted by [Zscheischler et al. \(2014c\)](#). However,  
499 the exponent varied significantly for different drivers with the range of 1.49–2.09 for TRENDY  
500 models and 1.69–2.39 in Yao-GPP ([Fig. 6](#)). In addition, the power law exponent for drought-  
501 induced extreme events were significantly smaller than for wet-related events. It means drought

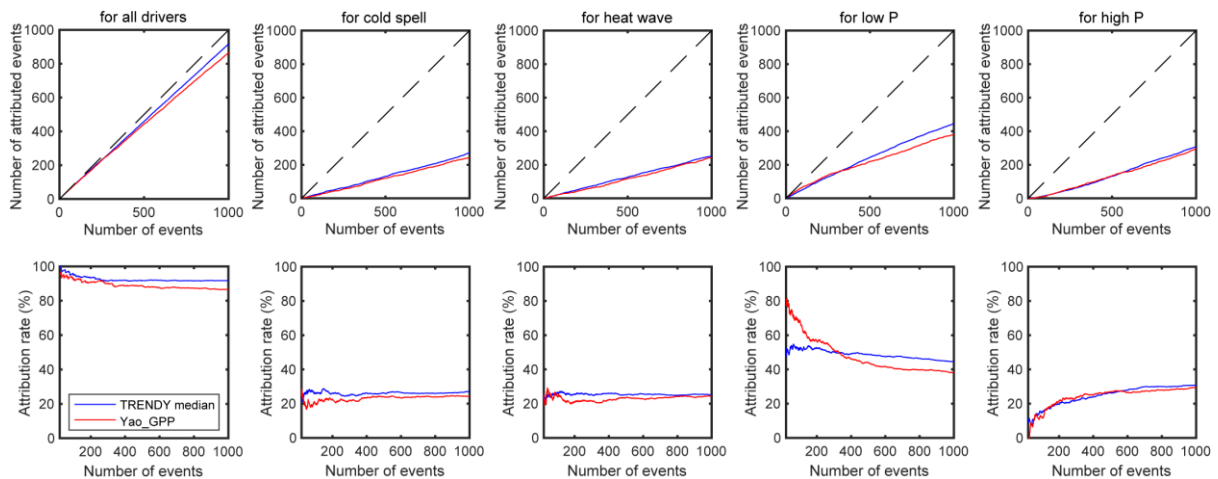
502 events are more likely to result in relative large events while wet events provoke less GPP  
503 response. It was also supported by the plot between number of studied largest extreme events  
504 and attribution rate for P, SM and scPDSI indices (Figs. 8 and A.7). When we increased the  
505 number of studied events (i.e. when looking into the smaller events), the attribution rate shows  
506 significant decreases for all drought indices but increase for all wet indices. A case study in  
507 Inner Mongolia grassland ecosystems demonstrated that both aboveground net primary  
508 productivity and CO<sub>2</sub> fluxes in the semiarid steppe were very stable in the face of extreme large  
509 precipitation events, regardless of the timing of the events (Hao et al., 2017). In contrast,  
510 multiyear precipitation reduction over northern China significantly decreased water availability,  
511 indicated by the Palmer Drought Severity Index and soil moisture measurements, and further  
512 resulted in strong decreases in carbon uptake (Yuan et al., 2014). Therefore, the lower  
513 sensitivity of vegetation to wet events than to droughts in our results (Fig. 7) could explain the  
514 more decisive role of droughts for negative GPP events. Based on multiple terrestrial models,  
515 Zscheischler et al. (2014b) also suggested higher drought impacts on GPP anomalies, partially  
516 during compound hot and dry conditions. The  $\alpha_m$ -value for fire-induced extreme events is much  
517 lower than for climate drivers, implying that GPP in China is less vulnerable to fire than to  
518 climate extremes.

519 The on-going global warming increased extreme climate events are an increasing threat  
520 to vegetation productivity in the future (Frank et al., 2015). It has been suggested that warm  
521 extremes are more frequent and more persistent in a +2 °C global warming scenario based on  
522 29 climate models, especially in southern China (Sui et al., 2018). Accordingly, we could  
523 predict that southern China has to face more heat wave-induced GPP negative anomalies as it  
524 is highly vulnerable to warm extremes. The effect of cold spells in southern China is more  
525 noticeable but received less attentions than droughts. Liu et al. (2018) found that the extension  
526 of the growing season in the Northern Hemisphere may actually make plant in fact more  
527 vulnerable to frost days, which further highlights the important role of cold spell. In addition,  
528 increases in the total amount and frequency of wet extremes are projected over most regions of  
529 China, particularly in QTP (Niu et al., 2017; Sui et al., 2018), which we expect have less  
530 negative impacts on vegetation productivity of grasslands there. An experimental study showed  
531 that grassland plant diversity increases the resistance of ecosystem productivity to climate  
532 extremes (Isbell et al., 2015), which provides a potential strategy to face future climate  
533 extremes for a large area of grasslands in northern China. Both TRENDY models and Yao-GPP  
534 showed that less GPP deficits were observed in Sichuan basin (Fig. 1), where croplands are the  
535 dominant vegetation type, possibly implying the importance of management for mitigating  
536 damage from climate extremes. Nevertheless, we still could not rule out the damage of climate  
537 extremes on croplands as evidence also showed that droughts and heat wave episodes  
538 significantly reduced global and national crop production with a reduction in both harvested  
539 area and yields (Lesk et al., 2016; Piao et al., 2010). For instance, Lobell et al. (2012) argued  
540 that warming presented an even greater challenge to wheat than implied by previous modeling  
541 studies.

542 However, there are still some limitations in this study. Firstly, we only consider time lags  
543 of a maximum of three months. There is evidence that extreme events can affect the carbon

544 cycle concurrently and produce lagged impacts at longer time scales (e.g. through vegetation  
 545 mortality) ([Arnone et al., 2008](#); [Schwalm et al., 2017](#)). This prolonged response of vegetation  
 546 GPP could be discovered in case studies but is rather difficult to be detected by our approach.  
 547 Secondly, there are ~10% of the GPP<sub>1000</sub> that did not correspond to any of the studied nine  
 548 factors. It is possible that compound events of less extreme conditions (e.g. T&P anomalies  
 549 within 10th-90th percentile) may also lead to extreme events in GPP. These confounding  
 550 factors may have an impact on the attribution analysis, especially for small events. That may  
 551 be the reason why there is a slight decrease in overall attribution rate from 95% for 100 events  
 552 to 92% for 1000 events in TRENDY and from 93% to 87% in Yao-GPP ([Fig. 8](#)). And the  
 553 interpolation to 0.1° from 0.5°-1° spatial-resolution datasets may also introduce uncertainty at  
 554 pixel scales. Finally, many factors also play important roles in regulating the vulnerability of  
 555 vegetation GPP to extreme events, for instance different ecosystems ([von Buttler et al., 2018](#);  
 556 [Xu et al., 2016](#)), management practices ([He et al., 2016](#)), and soil conditions ([Nepstad et al.,  
 557 2007](#)). Thus, future studies considering more drivers and regional conditions are necessary to  
 558 better understand the vulnerability and sensitivity of regional vegetation GPP to extreme events  
 559 in China. From this, detailed management practice is possible to be carried out to mitigate the  
 560 damage from future extreme events.

561



562

563 **Fig. 8.** Attribution rate for different number of studied largest GPP events and for each driver.

564

## 565 **5. Conclusion**

566 In this study, we investigated GPP extreme events in China and sub-regions based on a  
 567 spatio-temporally contiguous approach using the 5th percentile definition with GPP data from  
 568 12 process-based ecosystem models and one observation-based model. Both types of models  
 569 exhibited that vegetation in Northeast China and North China were most vulnerable to extreme  
 570 events, especially in mountainous regions. Over the past three decades, 45% and 68% of GPP  
 571 deficits in China occurred in summer in TRENDY models and Yao-GPP, respectively. Low  
 572 precipitation was associated with most extreme events among studied nine climatic drivers in  
 573 China in TRENDY models. Vegetation in southern China is more vulnerable to temperature  
 574 extremes (i.e. cold spell and heat wave) than in northern China. The importance of cold spells  
 575 is notable as they have received less attention than droughts in previous studies. Both power

576 law distribution analyses and sensitivity analysis highlight the impacts of drought on large GPP  
577 negative anomalies. Our results implied that policymakers could pay more attention to GPP  
578 deficits in northern China under drought events and in southern China under temperature  
579 extremes in order to mitigate the potential impacts of future climate extremes.

580

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588

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814

815 **Appendices**

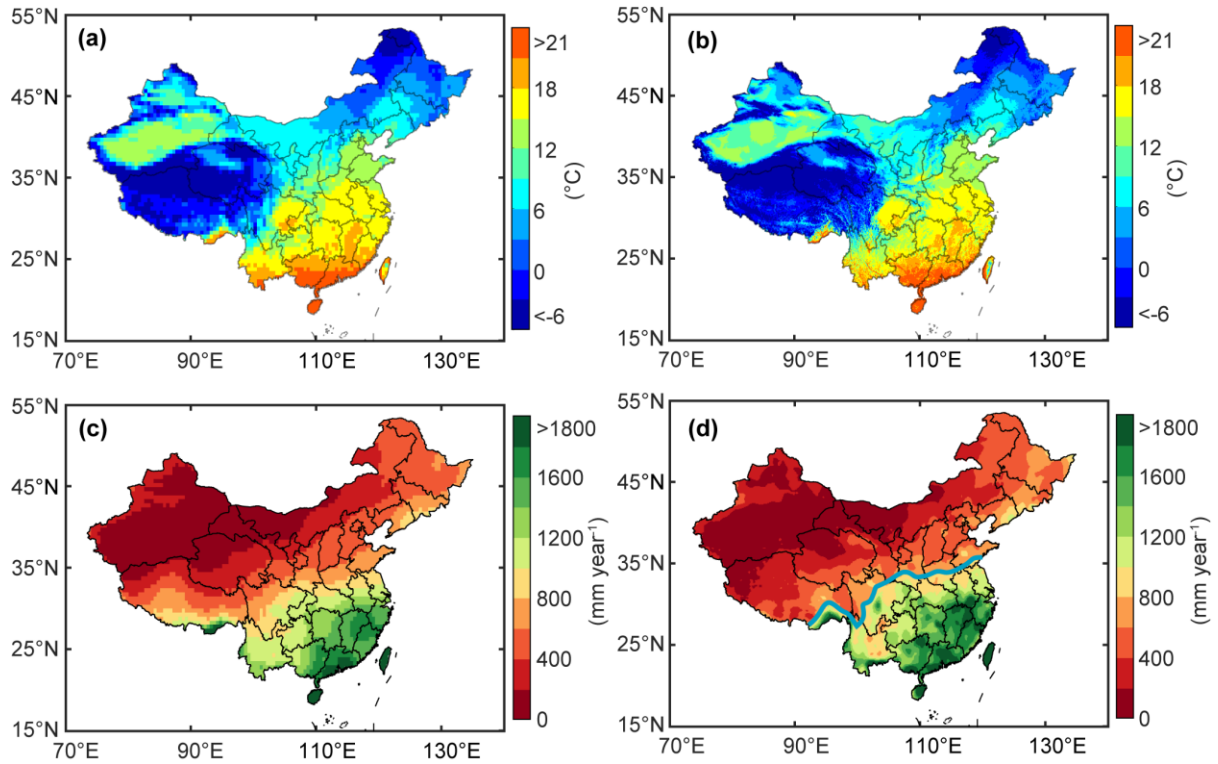
816

817 **Figure Legends**

818

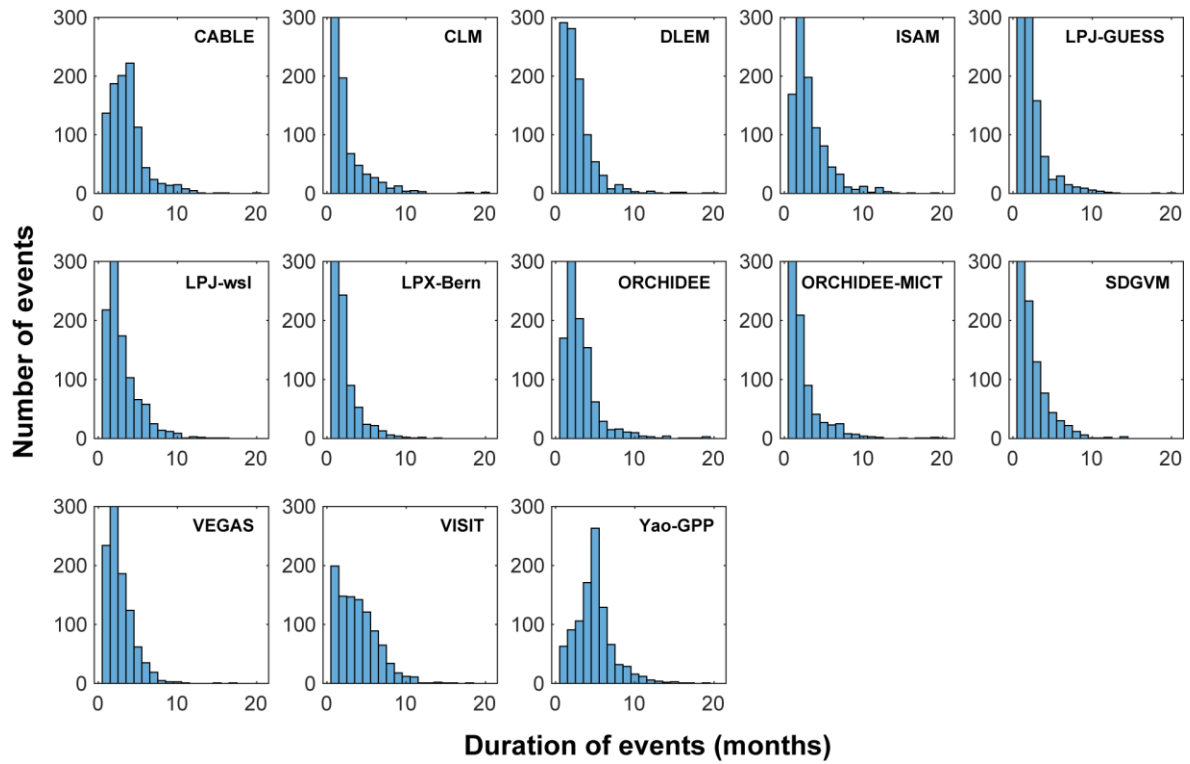
819 **Fig. A.1** The spatial distributions of (a, b) mean annual temperature and (c, d) mean annual  
820 precipitation for the period of 1982-2015 with (a, c) CRU and (b, d) ITPCAS data. The blue  
821 line in panel (d) denotes the 800-mm annual precipitation line of China, which separates China  
822 into northern and southern China.

823



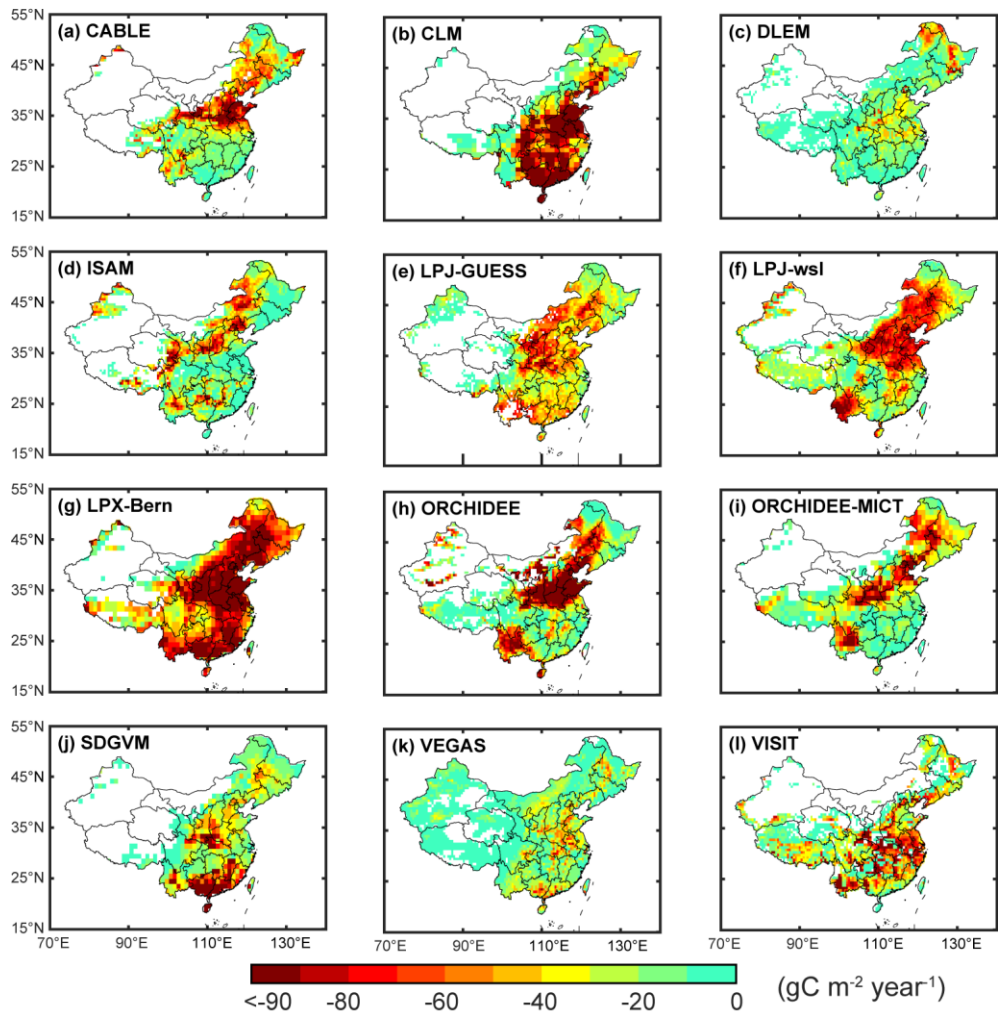
824

825 **Fig. A.2** The distribution of duration of the 1000 largest negative extreme events for each GPP  
826 data.  
827

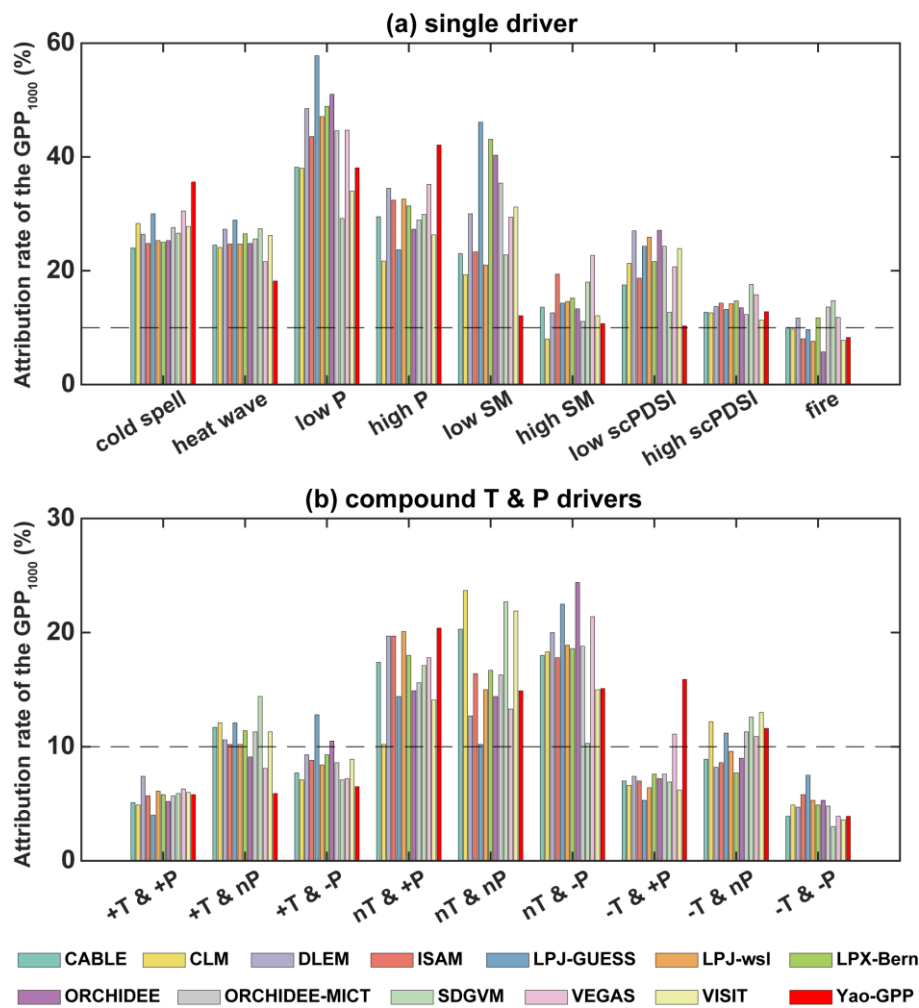


828

829 **Fig. A.3** The spatial distributions of negative extreme events in GPP during 1982-2015 for the  
 830 12 process-based TRENDY models. The 1000 largest negative extreme events were calculated  
 831 using the 5th percentile definition. White areas indicate no data.  
 832

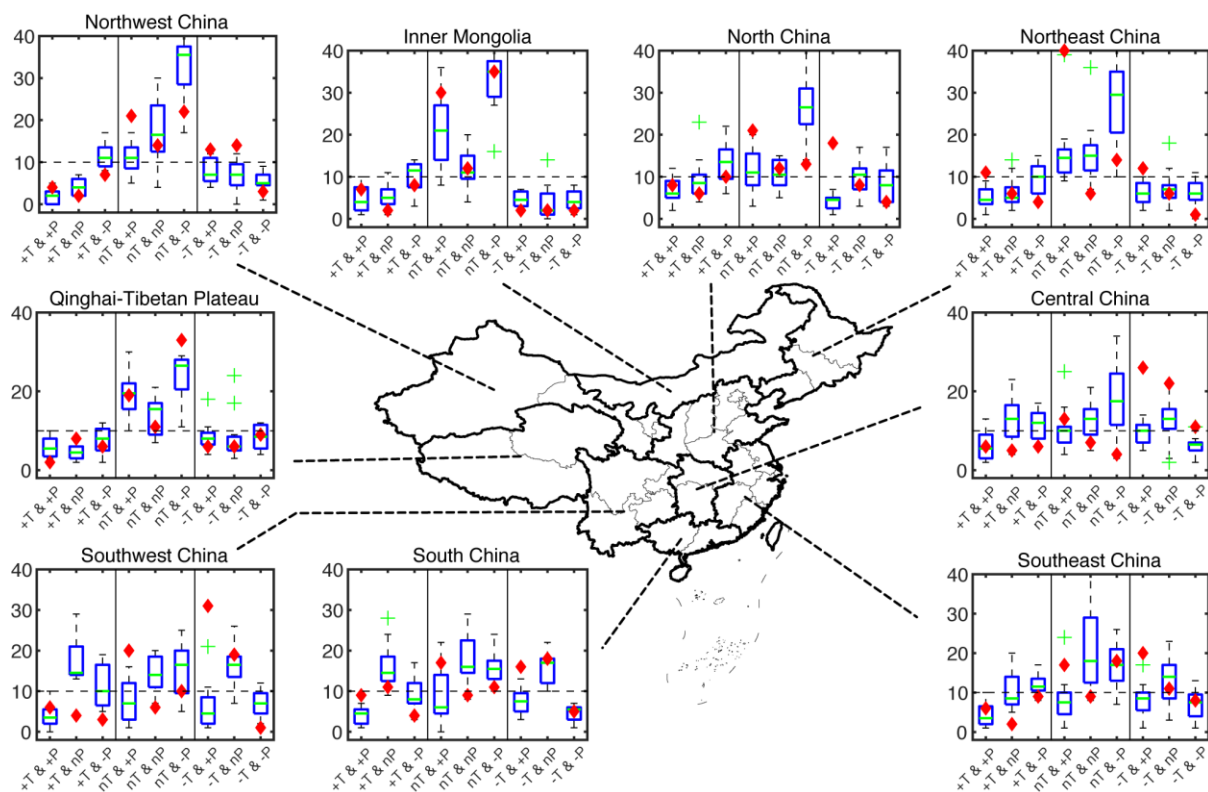


834 **Fig. A.4** The bar graph to show the attribution of the 1000 largest extreme events in China for  
 835 each model.  
 836



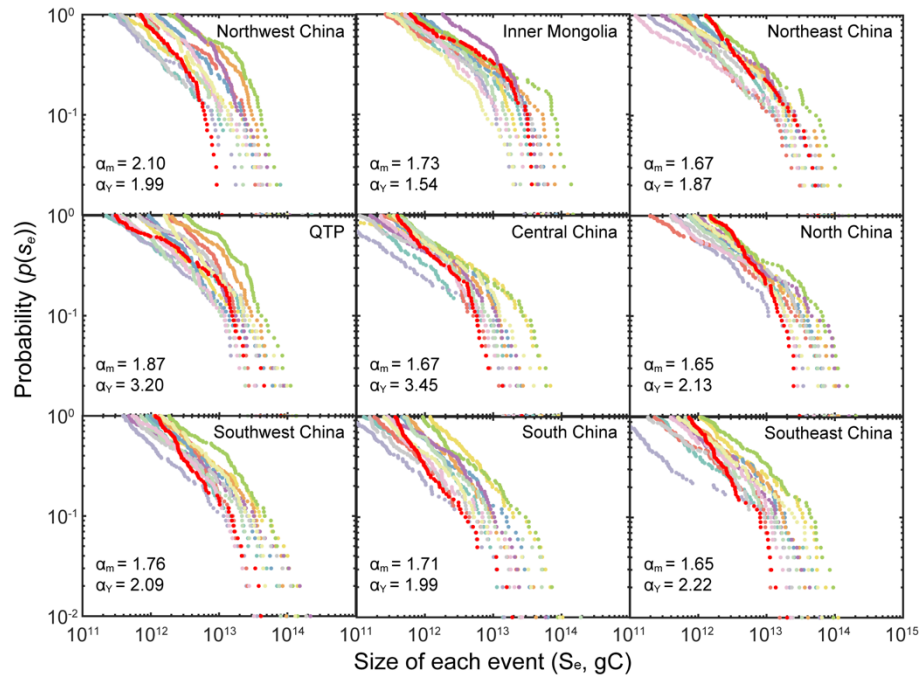
837  
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840 **Fig. A.5** Attribution rate of GPP extreme events to compound T&P effects for the nine sub-  
 841 regions of China. The largest 100 negative extreme events were used for each sub-region.  
 842



844 **Fig. A.6** The probability distributions of sizes of extreme events for the nine sub-regions of  
 845 China. The color legend to distinguish datasets is the same as Fig. 2. The letter  $\alpha_m$  and  $\alpha_Y$  are  
 846 median of the fitted exponents over the 12 process-based models and exponent for Yao-GPP,  
 847 respectively. The power law fitting and goodness-of-fit parameters are presented in Table A.3.  
 848 The color legend to distinguish GPP datasets is the same as Fig. A.4.

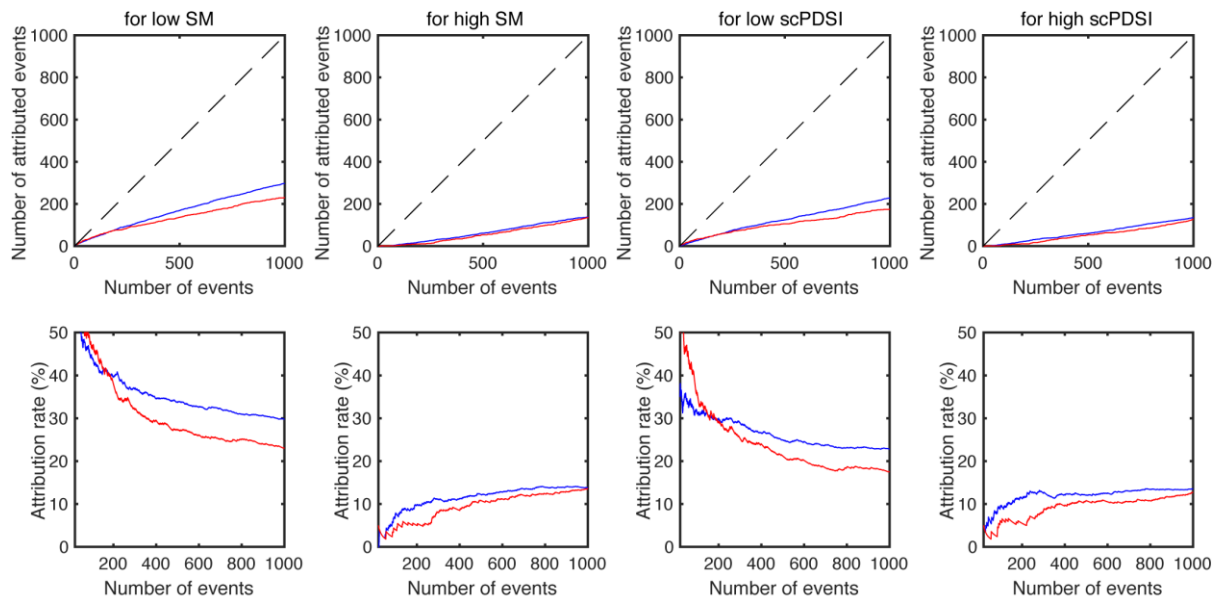
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851 **Fig. A.7** Attribution rate for different number of studied largest GPP events and for different  
852 drivers.

853



854

855



856 **Tables**

857

858 **Table A.1** Information on the 12 process-based TRENDY models used in this study.

859

Model	Long name	Spatial Resolution	Reference
CABLE	The CSIRO Atmosphere Biosphere Land Exchange Model	$0.5^\circ \times 0.5^\circ$	( <a href="#">Haverd et al., 2017</a> )
CLM4.5	Community Land Model version 4.5	$0.9375^\circ \times 1.25^\circ$	( <a href="#">Oleson et al., 2013</a> )
DLEM	Dynamic Land Ecosystem Model	$0.5^\circ \times 0.5^\circ$	( <a href="#">Tian et al., 2015</a> )
ISAM	Integrated Science Assessment Model	$0.5^\circ \times 0.5^\circ$	( <a href="#">Jain et al., 2013</a> )
LPJ-GUESS	Lund-Potsdam-Jena Dynamic Global Vegetation Model	$0.5^\circ \times 0.5^\circ$	( <a href="#">Smith et al., 2014</a> )
LPJ-wsl	Lund-Potsdam-Jena Dynamic Global Vegetation Model	$0.5^\circ \times 0.5^\circ$	( <a href="#">Sitch et al., 2003</a> )
LPX-Bern	Land surface Processes and eXchanges version 1.3	$1^\circ \times 1^\circ$	( <a href="#">Keller et al., 2017</a> )
ORCHIDEE	Organizing Carbon and Hydrology in Dynamic Ecosystems Land Surface Model	$0.5^\circ \times 0.5^\circ$	( <a href="#">Krinner et al., 2005</a> )
ORCHIDEE-MICT	Organizing Carbon and Hydrology in Dynamic Ecosystems Land Surface Model	$1^\circ \times 1^\circ$	( <a href="#">Guimberteau et al., 2018</a> )
SDGVM	Sheffield Dynamic Global Vegetation Model	$1^\circ \times 1^\circ$	( <a href="#">Woodward et al., 1995</a> )
VEGAS	Vegetation Global Atmosphere Soils	$0.5^\circ \times 0.5^\circ$	( <a href="#">Zeng et al., 2005</a> )
VISIT	Vegetation Integrative Simulator for Trace Gases	$0.5^\circ \times 0.5^\circ$	( <a href="#">Kato et al., 2013</a> )

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861 **Table A.2** The power-law fits and the corresponding p-values for extreme events induced by different drivers in Fig. 6. The letters of ‘n’, ‘a’ and  
862 ‘p’ denote the sample size, the exponent of the fitted power law and p-value, respectively. The statistically significant values where p-value > 0.1  
863 are denoted in bold.  
864

	Cold spell			Heat wave			Low P			High P			Low SM			High SM			Low scPDSI			High scPDSI			Fire		
	n	a	p	n	a	p	n	a	p	n	a	p	n	a	p	n	a	p	n	a	p	n	a	p	n	a	p
CABLE	240	1.70	<b>0.86</b>	245	1.67	<b>0.92</b>	382	1.51	0.06	295	2.10	<b>0.39</b>	175	1.47	<b>0.36</b>	127	1.87	0.05	196	1.49	<b>0.79</b>	146	2.17	<b>0.12</b>	56	2.06	<b>0.97</b>
CLM4.5	283	1.89	<b>0.10</b>	241	1.74	0.06	380	1.67	<b>0.22</b>	217	1.97	<b>0.44</b>	213	1.71	<b>0.15</b>	126	2.16	<b>0.27</b>	256	1.46	<b>0.61</b>	118	2.05	<b>0.69</b>	52	2.16	<b>0.18</b>
DLEM	264	1.66	<b>0.91</b>	273	1.74	<b>0.48</b>	485	1.73	<b>0.43</b>	345	1.72	<b>0.45</b>	270	1.76	<b>0.86</b>	137	1.67	0.02	297	1.66	0.02	149	1.78	<b>0.40</b>	72	3.05	<b>0.89</b>
ISAM	248	1.55	0.04	247	1.61	<b>0.17</b>	436	1.53	0.02	324	1.81	<b>0.35</b>	187	1.54	0	143	1.70	<b>0.25</b>	181	1.56	0.01	159	1.74	<b>0.63</b>	44	2.09	<b>0.78</b>
LPJ-GUESS	300	1.80	<b>0.78</b>	289	1.74	<b>0.77</b>	578	1.61	<b>0.25</b>	237	1.87	<b>0.95</b>	243	1.53	<b>0.49</b>	132	1.89	<b>0.50</b>	257	1.52	<b>0.22</b>	127	1.78	<b>0.99</b>	55	2.19	<b>0.83</b>
LPJ-wsl	253	1.66	0.04	247	1.57	<b>0.67</b>	471	1.55	0.06	326	1.92	<b>0.59</b>	259	1.52	<b>0.31</b>	142	1.75	0.05	229	1.52	0	165	1.92	0.02	39	2.51	<b>0.81</b>
LPX-Bern	250	1.72	<b>0.21</b>	265	1.77	<b>0.90</b>	489	1.65	<b>0.36</b>	314	1.87	<b>0.95</b>	216	1.72	<b>0.75</b>	147	1.80	<b>0.86</b>	221	1.48	<b>0.11</b>	146	1.85	<b>0.47</b>	65	2.15	<b>0.71</b>
ORCHIDEE	253	1.70	<b>0.80</b>	248	1.65	<b>0.47</b>	510	1.63	<b>0.14</b>	273	2.18	<b>0.91</b>	271	1.50	0.06	135	2.15	<b>0.54</b>	277	1.55	<b>0.44</b>	145	2.15	<b>0.16</b>	31	2.63	0.08
ORCHIDEE-MICT	276	1.65	<b>0.78</b>	256	1.70	<b>0.74</b>	446	1.51	0.03	289	1.80	<b>0.75</b>	243	1.51	0.06	123	1.86	<b>0.92</b>	243	1.40	0.06	117	1.94	<b>0.85</b>	72	2.17	<b>0.10</b>
SDGVM	266	1.75	<b>0.32</b>	274	1.76	0.03	292	1.70	<b>0.76</b>	299	1.82	<b>0.93</b>	127	1.66	<b>0.20</b>	176	1.70	0.01	168	1.68	<b>0.60</b>	192	1.82	<b>0.80</b>	87	2.59	<b>0.93</b>
VEGAS	305	1.55	<b>0.24</b>	216	1.56	0	447	1.60	0.04	352	1.65	0.03	207	1.51	0	158	1.68	<b>0.64</b>	220	1.50	0.02	167	1.70	<b>0.45</b>	65	2.10	<b>0.50</b>
VISIT	278	1.59	0.02	262	1.69	<b>0.75</b>	340	1.60	<b>0.59</b>	263	1.83	<b>0.63</b>	239	1.53	<b>0.51</b>	113	1.75	<b>0.26</b>	237	1.54	<b>0.14</b>	120	1.75	<b>0.60</b>	42	2.23	<b>0.29</b>
Yao-GPP	356	1.87	0	182	1.75	<b>0.43</b>	381	1.84	<b>0.44</b>	421	1.71	0.01	103	2.09	<b>0.96</b>	128	2.18	<b>0.93</b>	123	2.18	<b>0.28</b>	116	2.22	0.06	46	2.23	<b>0.78</b>

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867 **Table A.3** The power-law fits and the corresponding p-values for extreme events in different sub-regions in Fig. A.3. The letters of ‘n’, ‘a’ and ‘p’  
868 denote the sample size, the exponent of the fitted power law and p-value, respectively. The statistically significant values where p-value > 0.1 are  
869 denoted in bold.  
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	Northeast China			Inner Mongolia			Northwest China			North China			Central China			QTP			Southeast China			South China			Southwest China		
	n	a	p	n	a	p	n	a	p	n	a	p	n	a	p	n	a	p	n	a	p	n	a	p	n	a	p
CABLE	100	2.29	<b>0.58</b>	100	1.54	0.06	100	1.76	<b>1</b>	100	1.63	0.02	100	1.69	<b>0.14</b>	100	1.47	0.06	100	1.66	<b>0.59</b>	100	1.52	0.01	100	1.79	0.02
CLM4.5	100	1.50	0.01	100	3.12	<b>0.63</b>	100	1.61	0	100	1.70	<b>0.13</b>	100	3.36	<b>0.51</b>	100	1.71	<b>0.19</b>	100	1.68	<b>0.27</b>	100	1.78	0.09	100	1.65	0.07
DLEM	100	1.82	<b>0.16</b>	100	2.03	0.01	100	2.34	<b>0.17</b>	100	1.69	0.02	100	1.49	<b>0.21</b>	100	1.61	0.01	100	1.57	0.03	100	1.64	<b>0.23</b>	100	1.73	<b>0.22</b>
ISAM	100	1.86	<b>0.43</b>	100	1.45	0	100	1.54	0	100	1.78	<b>0.10</b>	100	3.04	<b>0.52</b>	100	5.06	<b>0.26</b>	100	1.61	0	100	1.72	<b>0.18</b>	100	2.35	<b>0.20</b>
LPJ-GUESS	100	1.71	0.05	100	1.63	<b>0.12</b>	100	1.82	0.01	100	1.63	0.06	100	1.59	0	100	2.13	<b>0.92</b>	100	1.59	0	100	1.70	0.04	100	1.67	0.01
LPJ-wsl	100	1.57	0.01	100	4.83	<b>0.61</b>	100	10.82	<b>0.80</b>	100	1.82	<b>0.17</b>	100	1.57	0	100	2.56	<b>0.24</b>	100	1.70	0.01	100	1.78	0.01	100	1.72	0.04
LPX-Bern	100	1.66	0.05	100	1.49	0.05	100	4.66	<b>0.80</b>	100	1.64	0.01	100	1.58	<b>0.27</b>	100	3.05	<b>0.82</b>	100	1.59	0.01	100	1.71	<b>0.17</b>	100	2.19	<b>0.44</b>
ORCHIDEE	100	2.27	<b>0.20</b>	100	6.61	<b>0.89</b>	100	2.76	<b>0.94</b>	100	1.61	<b>0.12</b>	100	2.12	0.08	100	2.48	<b>0.98</b>	100	2.19	0.08	100	2.54	<b>0.40</b>	100	1.54	0.03
ORCHIDEE-																											
MICT	100	1.59	0.05	100	1.54	0.01	100	1.74	<b>0.60</b>	100	1.49	0.01	100	2.49	0.04	100	1.92	0.01	100	1.92	0.03	100	1.66	0.02	100	2.04	<b>0.84</b>
SDGVM	100	1.69	<b>0.10</b>	100	4.77	<b>0.93</b>	100	1.87	<b>0.20</b>	100	1.66	0.02	100	1.87	0.09	100	1.67	0.02	100	1.80	0.02	100	1.79	<b>0.64</b>	100	1.71	0.07
VEGAS	100	1.50	0.03	100	1.81	0.07	100	2.34	<b>0.83</b>	100	1.59	0	100	1.65	0.01	100	1.80	0.01	100	1.64	0.01	100	1.76	0.09	100	1.81	0.01
VISIT	100	1.55	0	100	1.64	0.01	100	2.54	<b>0.93</b>	100	2.79	<b>0.81</b>	100	1.61	0.01	100	1.83	<b>0.25</b>	100	1.60	0.03	100	1.68	<b>0.10</b>	100	2.35	<b>0.28</b>
Yao-GPP	100	1.87	<b>0.38</b>	100	1.54	0	100	1.99	0.01	100	2.13	<b>0.10</b>	100	3.45	<b>0.96</b>	100	3.20	<b>0.72</b>	100	2.22	<b>0.18</b>	100	1.99	<b>0.65</b>	100	2.09	<b>0.18</b>

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