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1 **Title:** Exacerbated drought impacts on global ecosystems due to structural overshoot

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15

16 **Abstract**

17 Vegetation dynamics are affected not only by the concurrent climate, but also by memory-induced
18 lagged responses. For example, favorable climate in the past could stimulate vegetation growth to
19 surpass the ecosystem carrying capacity, leaving an ecosystem vulnerable to climate stresses. This
20 phenomenon, known as structural overshoot, could potentially contribute to worldwide drought
21 stress and forest mortality, but the magnitude of the impact is poorly known due to the dynamic
22 nature of overshoot and complex influencing timescales. Here we use a dynamic statistical learning
23 approach to identify and characterize ecosystem structural overshoot globally, and quantify the
24 associated drought impacts. We find that structural overshoot contributed to around 11% of
25 drought events during 1981-2015, and is often associated with compound extreme drought and
26 heat, causing faster vegetation declines and greater drought impacts compared to non-overshoot
27 related droughts. The fraction of droughts related to overshoot is strongly related to mean annual
28 temperature, with biodiversity, aridity, and land cover as secondary factors. These results highlight
29 the large role vegetation dynamics play in drought development, and suggest that soil water
30 depletion due to warming-induced future increases in vegetation could cause more frequent and
31 stronger overshoot droughts.

32

33

34 **Introduction**

35 Droughts have a large impact on global terrestrial ecosystems and the associated carbon and water
36 cycles¹⁻⁴. The impact of drought is dependent not only on the direct effects of concurrent climate
37 anomalies^{5,6}, but also on the ecosystem state, which itself is conditioned by antecedent climate^{7,8}.
38 For example, a period that is favorable to growth but followed by a water deficit can first stimulate
39 biomass accumulation, and as a result, further deplete soil moisture and increase drought risks.
40 This sequence of events represents a class of state dynamics known as structural overshoot⁹, where
41 an ecosystem temporarily exceeds the time-varying, climatologically-defined baseline carrying
42 capacity and in the process depletes potentially limiting water resources. Several previous studies
43 examined the lagged impact of structural overshoot for specific drought events and regions^{7,8,10,11}.
44 Understanding of the global occurrence and impact of structural overshoot is limited, however, as
45 ecosystem states are conditioned across multiple different time scales, and both the timescales of
46 importance and the ecosystem states change over time. This lack of a global understanding of
47 overshoot constitutes a large uncertainty in understanding drought development and its impacts on
48 vegetation dynamics as well as the global carbon and water cycles.

49
50 Here, we use a Bayesian dynamic linear model (DLM) approach¹², in combination with long-term
51 (1981-2015) satellite observations, high-resolution climate data, and a random forest analysis, to
52 characterize droughts related to structural overshoot (referred to throughout as overshoot droughts)
53 across global ecosystems and examine their impact on terrestrial vegetation-water relations
54 (Extended Data Fig. 1,2, Methods). In this study, we characterize drought events using a
55 combination of climatological drought index and associated vegetation greenness decline
56 represented by normalized difference vegetation index (NDVI¹³, Methods). While structural

57 overshoot has been examined in the context of regional forest mortality⁹, here we consider a
58 broader range of global ecosystems and negative lagged impacts on vegetation (Methods). The
59 DLM method allows for the decomposition of satellite-retrieved NDVI time series, into multiple
60 components (trend, seasonal, and de-seasonalized and detrended anomalies) through a Kalman
61 filtering process (see Methods). The anomaly components consist of the direct drought stress,
62 temperature, and direct and lagged effects from past vegetation anomalies at different time scales
63 (sub-seasonal, seasonal, intra-annual and inter-annual). This approach allows for the separation of
64 the timescales of importance for all drought events globally, which enables us to robustly identify
65 and characterize the role of structural overshoot in the timing, speed, frequency and impact of
66 drought (see Methods, Supplementary Text S1-4).

67

68 **Spatial patterns of overshoot droughts**

69 Our approach quantifies the spatial distribution of the number of droughts and those related to
70 structural overshoot during 1981-2015 (Fig. 1a,b). Globally, 11.2% of the drought events are
71 overshoot related, and lagged adverse effects explain 34.7% of the NDVI declines for these
72 overshoot drought events. The number of overshoot droughts generally follows the spatial
73 distribution of droughts ($r=0.45$, $p<0.001$, t-test), with exceptions in southern central US, northeast
74 Brazil and Australia, where overshoot occurrence relative to drought numbers is low. Spatial
75 autocorrelation does not show strong influence on this covariation and is therefore not considered
76 further in our analysis (Supplementary Text S5, Fig. S2). The fraction of drought events related to
77 overshoot shows a clear latitudinal pattern, with a decreasing trend from north to south (Fig. 1c,
78 Supplementary Fig. S3). Overshoot droughts are influenced by lagged adverse effects at different
79 time scales (Extended Data Fig. 3), with a strong dependence on growing season length (Extended

80 Data Fig. 4). The sub-seasonal scale overshoot component contributes most to the global overshoot
81 events, especially in northern high latitudes¹⁰. Lagged adverse effects from the sub-seasonal scale
82 also have the largest impact on NDVI decline (51.8%), which also dominates hotspot regions such
83 as boreal ecosystems in Alaska and Siberia, and agroecosystems in North China Plain and northern
84 India (Fig. 1d,e, Extended Data Fig. 3).

85

86 **Controlling factors and underlying mechanisms**

87 To understand which factors contribute to the number and impact of overshoot droughts, we build
88 a random forest model using various climate variables and ecosystem characteristics to predict the
89 spatial pattern of fraction of drought related to overshoot and fraction of lagged adverse effects to
90 total drought impact (see Methods). The resulting models can explain 63.9% and 50.5% of the
91 spatial out-of-bag variance for the fraction of overshoot number and impact, respectively. Based
92 on these models, we obtain the rank importance of variables that drive these spatial patterns, and
93 the partial dependence of the fraction of overshoot number and impact along each variable (Fig.
94 2).

95

96 Overshoot droughts are more prevalent in stressed or seasonally stressed environments, usually
97 with a shorter growing season (Fig. 2k). Positive climate anomalies in stressed environments can
98 act as a stimulus for vegetation growth, allowing temporary exceedance of climatologically-
99 defined ecosystem carrying capacity. Temperature stress, in comparison to water stress, can lead
100 to more frequent and greater impacts of overshoot drought events (Fig. 2a,h). In cold regions (mean
101 annual temperature less than 0°C), temperature is the primary limiting factor for both vegetation
102 phenology and productivity during the entire growing seasons^{14,15}. A positive temperature anomaly

103 in the early growing season exponentially increases water consumption¹⁶, potentially leading to
104 higher drought risk and stronger lagged effect. In comparison, mean annual precipitation plays a
105 less important role. This is likely due to the fact that soil water is mostly low and has limited
106 buffering capacity in dry regions, ecosystems are therefore more responsive to concurrent
107 precipitation anomalies and relatively less dependent on the lagged effect¹⁷. As expected, the
108 number and impact of overshoot drought events also increases with larger interannual variations
109 of mean annual temperature (MAT) but much less with precipitation (Fig. 2b,f). Increases in
110 climate variability not only increase the chances of a more favorable environment for plant growth
111 in earlier periods, but also induce more frequent extreme heat and dry anomalies, leading to water
112 deficit and potential drought.

113

114 Ecosystem biodiversity also plays a critical role in regulating overshoot drought occurrence. The
115 number and impact of overshoot droughts decrease when the number of native species is greater
116 than 500 (Fig. 2d). Low biodiversity is associated with synchronous plant behavior (e.g., expansive
117 growth when the environment is favorable, and soil water depletion at similar rooting depths¹⁸). In
118 addition, ecosystems with low biodiversity are expected to have weaker drought resistance, and
119 thus lagged adverse effects tend to have a greater proportional impact¹⁹. Vegetation coverage,
120 represented by mean annual NDVI, also positively affects the number of overshoot drought events
121 (Fig. 2g). Higher vegetation coverage increases the plants' role in linking the energy and water
122 fluxes between soils and the atmosphere²⁰. Anomalies in high vegetation coverage ecosystems
123 would therefore have a greater impact on soil water and are more likely to induce a lagged adverse
124 effect. Land cover type also plays an important role, with a higher number and impact of overshoot
125 drought events for boreal forest and woody savannas (Fig. 2e).

126

127 In contrast, soil characteristics (clay fraction), terrestrial water decay time estimated from Gravity
128 Recovery and Climate Experiment satellites (GRACE τ , Methods), and asynchronicity between
129 peak temperature and precipitation show little role in determining the number and impact of
130 overshoot drought events. We also test the robustness of these results by predicting the absolute
131 overshoot drought number and lagged effect instead of their fractions with two other random forest
132 models, and find similar environmental dependences (see Methods, Supplementary Fig. S4).

133

134 **Overshoot and compound drought and heat**

135 We further analyze the temporal occurrence of overshoot droughts. In the northern mid- to high-
136 latitudes ($>30^{\circ}\text{N}$), 51.2% overshoot drought events happen in July and August (Fig. 3a). For the
137 Southern Hemisphere, two peaks can be observed in March and September, which is likely due to
138 the double growing season experienced in many water-limited regions. This is also likely to occur
139 for parts of dry Mediterranean climate regions in the Northern Hemisphere, where overshoot
140 drought may happen in either peak growing season. We also compare the start date for overshoot
141 drought and non-overshoot droughts. To make these dates comparable across space, they are
142 normalized by the peak growing season, and the results are summarized in four aridity regions
143 (Fig. 3b-e). For dry regions, non-overshoot droughts are more likely to happen before the peak
144 growing season, while overshoot droughts are more likely to happen in the mid- to late growing
145 season. These significant differences in drought timing ($P<0.0001$, paired two-sided t-test) also
146 suggests that overshoot droughts are more likely to happen in warmer months, especially for semi-
147 arid and dry sub-humid regions (Fig. 3f-i, Extended Data Fig. 5a). Considering the positive
148 temperature anomalies during the drought period, overshoot droughts tend to have higher risk of

149 extreme temperature. This compound drought and heat can be detrimental to ecosystem
150 functioning and related ecosystem services, particularly for the mid-latitude semi-arid to dry sub-
151 humid regions²¹⁻²³, which are major crop production areas and densely populated.

152

153 **Overshoot and the development speed of drought impacts**

154 Globally, overshoot droughts are associated with a faster NDVI decline than non-overshoot
155 droughts ($P < 0.0001$, paired two-sided t-test) (Fig. 4). Similar patterns can also be found if
156 comparing the maximum NDVI decrease speed or the NDVI changes at the zero-crossing month
157 (Extended Data Fig. 6). This faster decrease in NDVI is often accompanied with larger differences
158 in NDVI anomalies between the start and end of the drought development period (Fig. 4b-g). Using
159 soil moisture data from ERA5 reanalysis²⁴ and a machine learning approach²⁵, we also find faster
160 soil moisture decline for overshoot droughts than non-overshoot droughts ($P < 0.0001$, paired two-
161 sided t-test) (Extended Data Fig. 7). However, the differences in soil moisture changes are much
162 smaller than the differences in vegetation declines ($P < 0.0001$, unpaired two-sided t-test),
163 potentially because the interannual variations of vegetation is not used as a forcing in these datasets,
164 and their effects on soil moisture may thus be underestimated.

165

166 Due to the rapid onset and intensification of vegetation deterioration, the majority of overshoot
167 droughts we identify can also be classified as flash droughts^{26,27}. Flash droughts occur most
168 frequently in mid latitude semi-arid or dry sub-humid regions where overshoot impacts are
169 dominated by the sub-seasonal and seasonal lagged effects (Extended Data Fig. 3). Most overshoot
170 droughts develop very quickly (mostly 2-3 months), and are on average 1-2 months shorter than
171 non-overshoot droughts in these semi-arid regions (Extended Data Fig. 8).

172

173 In addition, overshoot droughts usually lead to stronger drought impacts for dry sub-humid and
174 humid regions, as shown by a more negative NDVI anomaly compared to the standardized
175 precipitation evapotranspiration index (SPEI) anomaly (Extended Data Fig. 9). SPEI is a widely
176 used drought severity indicator which calculates the standardized surface water balance anomaly
177 from meteorological variables. To understand how overshoot modulates the drought severity
178 (assessed by minimum SPEI) and impact (assessed by minimum of standardized NDVI, $NDVI_z$)
179 relationship, we build three nested linear models to predict $NDVI_z$ anomalies from SPEI values
180 during droughts. The first model does not consider overshoot effect. The second considers the
181 effect on intercepts only, and the third considers the effect on both the regression slopes and
182 intercepts (Methods, Extended Data Fig. 10). The results from this model comparison can be
183 summarized into five types of severity-impact responses (see Methods, Fig. 5b). For about a
184 quarter of the area where the three models are evaluated, overshoot exacerbates drought impact to
185 the same degree across different drought severities (Type 1 in Fig. 5). The nested models predict
186 an additional $NDVI_z$ decline of -0.58 ± 0.30 . In another quarter of area, overshoot leads to stronger
187 impact when drought severity is low, causing a decrease of $NDVI_z$ by -0.07 ± 0.28 (Type 2 in Fig.
188 5). By contrast, only 3% of area indicates overshoot has stronger impact when drought severity is
189 high, with an additional $NDVI_z$ decline by -0.27 ± 0.24 (Type 3 in Fig. 5). Overshoot alleviates the
190 drought impact for only 4% of the area (Type 4 in Fig. 5). This may be due to a mismatch in timing
191 when drought or overshoot impact reach their maximum.

192

193 Our analysis, based on a dynamic statistical learning approach applied to long-term satellite
194 vegetation records, provides a global understanding of the role of vegetation structural overshoot

195 in the timing, speed and impact of drought events. Overshoot droughts are found to develop faster
196 and be more likely to compound with extreme heat than non-overshoot droughts, exacerbating the
197 drought impact on ecosystem function and the associated societal services. Overshoot droughts are
198 also expected to be associated with increased competition, changes in species composition and
199 functional groups. It is not possible however to analyze these ecological processes at global scales
200 in our study and they therefore warrant further analysis. Soil water balance may be the key to link
201 the lagged adverse effects, but land-atmosphere feedbacks^{28,29} and other processes such as plant
202 phenology^{30,31}, and fire disturbance play potentially important roles. Current drought indices,
203 including those relying on potential evapotranspiration, do not consider vegetation status in
204 calculating the water balance, may therefore underestimate drought severity when structural
205 overshoot happens. Global climate change can promote faster vegetation growth³² and soil water
206 depletion³³, together with more frequent and severe climate extremes, potentially increasing the
207 overshoot drought occurrence and impact. Continuous satellite monitoring and improved model
208 simulation are needed to help better understand the changes of overshoot and improve the
209 prediction of future drought impacts.

210

211 **Methods**

212 **GIMMS NDVI and Climate datasets**

213 We use the normalized difference vegetation index (NDVI) from GIMMS 3gv1 (1981-2015, ref¹³)
214 which provides long-term records for vegetation activity. NDVI is a remotely sensed indicator
215 based on the unique spectral characteristics of vegetation and has been demonstrated to be strongly
216 related to ecosystem leaf area index and photosynthetic capacity³⁴⁻³⁶. It can therefore represent the
217 aggregated ecosystem response to climatic anomalies and drought stress. This dataset is first
218 quality checked and aggregated to monthly $0.5^\circ \times 0.5^\circ$ resolution to match the resolution of other
219 datasets and to reduce the uncertainty. In many northern regions, the quality flags are not always
220 effective, especially when mixed snow pixels exist. Since the DLM is sensitive to these de-
221 seasonalized anomalies, and drought and water limitations are not likely to happen during these
222 cold and snow-covered periods, we therefore use an additional temperature threshold to filter out
223 these potential contaminated pixels: if the mean air temperature for a specific month is below 0°C ,
224 the land surface may be covered by snow and the corresponding NDVI is set to NA.

225

226 We use both precipitation and temperature as environmental variables in the DLM. The
227 precipitation dataset is from GPCC³⁷. This dataset provides monthly precipitation at a $0.5^\circ \times 0.5^\circ$
228 spatial resolution. The dataset is generated using a spatial statistical method based on observations
229 from global gauge network which extends beyond Global Historical Climatology Network
230 (GHCN). Compared to other precipitation datasets (for example, CRU TS4.04), this dataset uses
231 more stations and is often considered to be a more reliable estimate of precipitation at the global
232 scale³⁹. We use the monthly air temperature dataset from CRU TS 4.04 (ref³⁸). CRU generates
233 gridded climate dataset from weather station data and a spatial statistical method. We also use a

234 standardized precipitation evapotranspiration index (SPEI⁴⁰) dataset for drought identification and
 235 drought severity assessment. SPEI is a widely used climatological drought index that calculates
 236 the standardized water balance anomalies (precipitation minus potential evapotranspiration) at
 237 different time scales. It is therefore an optimal index to evaluate the drought severity-impact
 238 relationship and the role overshoot plays in this process. We use a 3-month SPEI dataset based on
 239 the CRU dataset so that it can capture the short-term water deficit.

240

241 **Bayesian multivariate dynamic linear model (DLM)**

242 The multivariate dynamic linear model is a type of linear model for time series analysis¹².
 243 Compared to a multivariate regression model, it allows the regression coefficients to change over
 244 time, which can better capture the time-varying relationship between vegetation status in the past
 245 and at present. This method was introduced by Harrison and Stevens⁴¹ and well documented by
 246 West and Harrison¹². In this study, we modify the model structure used by Liu et al. (ref⁴²), by
 247 further considering the lagged effect of vegetation anomalies from previous months along with
 248 concurrent climate anomalies. For each pixel, the DLM predicts the time series of the target
 249 variable (y_t , satellite retrieved NDVI) using an observation equation (Eq. 1) and a state evolution
 250 equation (Eq. 2):

$$251 \quad y_t = \mathbf{F}_t^T \boldsymbol{\theta}_t + v_t \quad (1)$$

$$252 \quad \boldsymbol{\theta}_t = \mathbf{G} \boldsymbol{\theta}_{t-1} + \mathbf{w}_t \quad (2)$$

253 where y_t is the observed NDVI at each month t after removing the mean. \mathbf{F}_t is a vector consisting
 254 of three components, a constant for local mean and trend ($\mathbf{F}_{trend} = [1,0]$), a constant for three
 255 seasonal components ($\mathbf{F}_{seas} = [1,0,1,0,1,0]$), and a regression component including the
 256 temperature, precipitation and NDVI anomalies (δ) from previous months which change with time

257 t ($\mathbf{F}_{reg,t} = [\delta\text{Temp}_t, \delta\text{Prec}_{t-1,t-3}, \delta\text{NDVI}_{t-1}, \delta\text{NDVI}_{t-2,t-3}, \delta\text{NDVI}_{t-4,t-6}, \delta\text{NDVI}_{t-7,t-12}, \delta\text{NDVI}_{t-13,t-24}]$).

258 The subscript of each variable indicates the starting and ending months used to calculate the mean
259 value, using the de-seasonalized and detrended temperature, precipitation and NDVI. We do not
260 consider radiation in this default model setup because the interannual variations of radiation is
261 small and can have strong correlation with temperature or precipitation at monthly scale. $\boldsymbol{\theta}_t$ is the
262 state vector at time t , which also consists of three components: coefficients representing local
263 mean and trend, coefficients representing seasonal dynamic and regression coefficients for the
264 previous months' precipitation and NDVI, as well as current month temperature. v_t is the state
265 evolution noise at time t assuming it has a zero mean with a Gaussian distribution. \mathbf{G} is a known
266 state evolution matrix that is block diagonally connected with three small matrices, corresponding
267 to the local mean and trend component, seasonal component, and regression component. \mathbf{w}_t is the
268 state evolution noise at time t , following a zero mean multivariate Gaussian distribution. Starting
269 with non-informative priors of $\boldsymbol{\theta}_0$ and noises of v_t and \mathbf{w}_t , we estimate the posterior distribution
270 of $\boldsymbol{\theta}_t$ using the forward filtering method. This method uses Kalman Filtering to get the posterior
271 of y_t , and takes a step further to back propagate the difference between prior and posterior
272 estimates of y_t to get the posterior distribution of $\boldsymbol{\theta}_t$. In this study, we focus on the posterior
273 estimates of the regression coefficients for the previous months' NDVI, named DLM sensitivities.
274 These sensitivities, together with the corresponding NDVI anomalies were used to identify
275 overshoot droughts. Since the DLM uses a Kalman Filter at each time step, in order to get a reliable
276 prediction of the coefficient, especially in the early study period, we use a "spin-up" period by
277 recycling the first five years (1981-1986) of satellite NDVI and climate observations two times
278 prior to the start of the dataset. It should be noted that although the model is a class of "linear
279 models", its sensitivities change through time, and thus can capture temporal non-linearity. A

280 detailed description of this method can be found in the Supplementary Text S1. In addition to this
281 “default model” setup which considers both temperature and precipitation in the regression
282 component, we also test a “reduced model” which does not consider temperature, and an “extended
283 model” that considers precipitation, temperature, and radiation. A detailed description on these
284 experimental setups together with other sensitivity analysis can be found in Supplementary Text
285 S2.

286

287 **Drought and overshoot identification**

288 We use a combination of SPEI and NDVI together with outputs from the DLM to identify drought
289 events. Both indices are directly calculated from observations and represent the climatological
290 drought severity and the drought impact on vegetation, respectively. After the NDVI time series
291 for each pixel is decomposed by the DLM, we identify all negative anomalies from the de-
292 seasonalized and detrended NDVI (original NDVI time series minus trend and seasonal
293 components obtained from DLM decomposition). For each consecutive negative NDVI anomaly,
294 a minimum value is first retrieved. A drought starts when the NDVI anomaly turns negative and
295 ends when the NDVI anomaly recovers above 70% of the minimum value. Three criteria need to
296 be met in order to be considered as a drought event: (1) drought should be at least two months long
297 and the minimum NDVI anomaly should be smaller (more negative) than 10% of the mean NDVI
298 in order to exclude events due to random noise in NDVI; (2) the average SPEI during the
299 corresponding period is below -0.5. It should be noted that we used a relaxed threshold for SPEI
300 (“-0.5” compared to commonly used “-1”), since overshoot droughts may happen with only
301 moderate precipitation decline; (3) the temperature component during the drought period should
302 be greater than the precipitation component (less negative) or the temperature sensitivity

303 (coefficient for δTemp_t) should be negative. This is to exclude the NDVI decline due to low
304 temperature rather than low soil water.

305

306 Overshoot in this study is defined as vegetation's temporary exceedance of the ecosystem carrying
307 capacity, which leads to increased soil water consumption and causes a lagged adverse effect on
308 latter vegetation activity due to water stress. It should be noted that because of the seasonal
309 dynamics of vegetation and climatic factors, the carrying capacity, i.e., the maximum plant canopy
310 that can be supported, is also time-varying. Soil water dynamics contain the overshoot information
311 but cannot be directly observed, so the approach we use to identify structural overshoot is to
312 examine the lagged adverse linkage between de-seasonalized anomalies of NDVI.

313

314 In practice, after drought events are identified for each pixel, we calculate the average NDVI
315 anomaly and DLM sensitivity during each drought period for each of the four previous-month
316 NDVI components, i.e., previous 2-3 months, previous 4-6 months, previous 7-12 months, and
317 previous 13-24 months (Extended Data Fig. 1). For each drought event, if any of the four previous-
318 month NDVI components have a positive anomaly associated with a significantly negative ($CI=0.9$)
319 sensitivity coefficient, that is, the total contribution (the product of NDVI anomaly and sensitivity)
320 to the prediction of current NDVI is negative, this NDVI component is regarded as an overshoot
321 component. For a drought event, if the summation of all overshoot component contributions is
322 greater than the non-overshoot contributions by absolute value, and the minimum of the overshoot
323 component is less than -0.01 , this drought event is considered as an overshoot drought event. Since
324 we use several arbitrary thresholds in the drought and overshoot drought identification, we also
325 test the uncertainties caused by the model structure and thresholds chosen. The results show that

326 different models and thresholds can affect the absolute number of droughts and overshoot droughts,
327 however, the spatial patterns are quite similar and the fraction of overshoot drought numbers to
328 total drought numbers is conservative, ranging from 9.93% to 18.49%, with a median value of
329 11.22%. Detailed information is provided in Supplementary Text S2, Table S1 and Fig. S5-11. In
330 addition to GIMMS NDVI, we also use NDVI from the Moderate Resolution Image Spectrometer
331 (MODIS) MOD13C2 and identify overshoot during 2000-2018. The resulting spatial patterns are
332 similar with those obtained using GIMMS NDVI (Fig. S12).

333

334 To understand the differences in development speed of drought impact between overshoot and
335 non-overshoot drought, we first define the drought impact development period which begins with
336 the monotonical decrease of the de-seasonalized detrended NDVI and ends when it reaches its
337 minimum within a drought event. Within each drought development period, we first calculate the
338 speed of changes as the differences in de-seasonalized detrended NDVI between months. We
339 compare three metrics to characterize the development speed of drought impact: the speed of
340 changes at its maximum (75 percentile), median (50 percentile) and at its zero-crossing month (i.e.,
341 when the drought starts).

342

343 **Timing of overshoot**

344 We identify the starting month for each drought event to examine drought timing. For each pixel,
345 the average starting months for overshoot and non-overshoot drought events are calculated
346 separately. We fit a probability density function (PDF) of the overshoot drought starting date for
347 each pixel and determined the months when the probability reaches its maximum. Since December
348 and January are also nearby months but the PDF cannot be correctly fitted under this condition,

349 we shift the starting date by 3- 6- 9- months and fitted three other PDFs. The final starting date is
350 determined by the months corresponds to the maximum probability across all four PDFs. If the
351 maximum probabilities for the four PDFs are the same, it indicates that the starting dates of
352 overshoot drought do not have any tendency and this pixel is not used. This only happens for a
353 very small proportion of the total area (~0.55%). To make these timings comparable across space,
354 we normalize the starting months of each drought event by the peak growing season. These
355 differences are then rescaled to -6 to +6 months.

356

357 **Drought impact assessment**

358 Drought impact on vegetation is often related to meteorological water deficit, however, this
359 relationship may be altered when overshoot happens. We use three nested models to assess the
360 overshoot impact on this relationship:

$$361 \quad NDVI_z = a \cdot SPEI3 + b \quad (3)$$

$$362 \quad NDVI_z = a \cdot SPEI3 + b \cdot overshoot + c \quad (4)$$

$$363 \quad NDVI_z = (a + c \cdot overshoot) \cdot SPEI3 + b \cdot overshoot + d \quad (5)$$

364 The first model (null model) only considers water deficit as indicated by 3-month SPEI. The
365 second model assumes that when overshoot happens, it will change the intercept of the regression.
366 The third model assumes that when overshoot happens, both the intercept and the sensitivity of
367 SPEI will change. Since there is a limited number of overshoot drought events for each pixel, we
368 evaluate these three models on $2.5^\circ \times 2.5^\circ$ windows, so that each window has at least 10 overshoot
369 droughts and 10 non-overshoot droughts during the study period. To make NDVI declines
370 comparable within each window, the NDVI declines are standardized by the standard deviation of
371 de-seasonalized detrended anomalies ($NDVI_z$, z-score). The best model is selected based on an

372 ANOVA comparison, second and third models are only selected when they are significantly better
373 than the first model ($p < 0.1$).

374

375 Based on the comparison of these three models, we categorize overshoot impact into five groups
376 (Fig. 5). (1) overshoot has no effect on the NDVI-SPEI relationship. This is considered when the
377 first model is chosen; (2) overshoot decreases the intercept of the NDVI response to SPEI, but the
378 NDVI response to SPEI remain the same. This is considered when second model is chosen and
379 coefficient b is negative; (3) overshoot decreases the intercept of the NDVI response to SPEI, but
380 the sensitivity of NDVI to SPEI is reduced. This is considered when the third model is chosen and
381 both coefficient b and c are negative. (4) overshoot increases the intercept of the NDVI response
382 to SPEI, and the sensitivity of NDVI to SPEI is increased. This is considered when the third model
383 is chosen and both coefficient b and c are positive. (5) overshoot alleviates the drought impact.
384 This is considered when all other cases happen. To assess the overshoot impact on drought, we
385 predict the effect related to overshoot based on the best model selected and average SPEI values
386 for all overshoot drought events within this $2.5^\circ \times 2.5^\circ$ window.

387

388 **Randomized experiment**

389 We set up a randomized experiment to test if the DLM can effectively capture the linkages between
390 the previous positive NDVI anomalies and current NDVI decline, that is, the overshoot. It has the
391 following four steps:

392 (1) Twelve months are grouped into 6 groups, with each group have two consecutive months
393 (e.g., January and February, March and April).

394 (2) NDVI, temperature, and 3-month precipitation and SPEI for each group are shuffled
395 together across years, so that the NDVI for each month still corresponds to the temperature
396 and precipitation for that month, and their relative positions within a year remain unchanged,
397 e.g., July and August from 2012 may be swapped to July and August, 1998, following May
398 and June from 2007.

399 (3) Using this randomized dataset, we again run the DLM model and identified the drought
400 and overshoot drought events for 1981-2015.

401 (4) This process is repeated 5 times with different random seed for the step (2). After the
402 drought and overshoot drought events are identified, we swap them back to their original
403 position so that they are comparable between randomized experiments. If three out of five
404 experiments identify any two months as a drought event, this event is considered as a valid
405 drought event. If three out of five experiments identify a drought event as an overshoot
406 drought event, this event is considered as a valid overshoot drought event.

407 We swap the months by 2-month group sizes because during the drought identification step, a
408 negative anomaly should be at least two-month long so that it can be considered as a potential
409 drought event. This step should have limited effect on drought identification since droughts are
410 identified based on NDVI with concurrent climate anomalies which are swapped together. In the
411 randomized experiment, however, this random swap is likely to break up most of the lagged effects.

412

413 We also test if the lagged effect can be partially retained if we choose larger group sizes. To do so,
414 instead of swapping the NDVI by two-month groups in step (1), we use larger group sizes of 6-
415 month, and 24-month during the swap. For example, March to August in 2012 will be moved
416 together to March to August in 1999 (6-month group) or September 2010 to August 2012 will be

417 moved together to September 1982 to August 1984 (24-month group). By using larger groups,
418 partial lagged effects may be retained, for example, the lagged effects at sub-seasonal scale may
419 be kept using the 6-month group size, and the effect at intra-annual scale may be kept if we use
420 24-month group size.

421

422 We find that when using a group size of two months, the spatial pattern of drought numbers does
423 not change much, while most of the overshoot droughts are no longer identified. With the increase
424 of the group sizes, more overshoot drought events are identified, and the spatial patterns become
425 similar to the one we obtained without randomization. This suggests the DLM can effectively
426 capture the lagged effect and help identify overshoot drought. More detailed information is
427 provided in Supplementary Text S3 and Supplementary Fig. S14-16.

428

429 **Synthetic data experiment**

430 We also generate a synthetic dataset to test if overshoot drought events can be effectively identified
431 using our methodology. To do this, we first build a simple vegetation model that considers both
432 the direct effect of environment and the lagged effect of previous months NDVI through soil water
433 dynamics (Supplementary Text S4). We focus on the 2012 overshoot drought in central US⁸. Using
434 this simple model, we set up four different scenarios to simulate vegetation dynamics, and applied
435 the overshoot identification algorithm used in this study:

436 (1) Control run, spring warming and low summer precipitation

437 (2) No spring warming, low summer precipitation

438 (3) Spring warming, normal summer precipitation

439 (4) Spring warming, abundant summer precipitation but with other disturbances

440 These four scenarios differ in their environmental drivers and, consequently, NDVI anomalies
441 simulated by the simple model. Based on the synthetic data, only Scenario 1 is considered as an
442 overshoot drought event, while for the other three, they either do not have a lagged adverse effect
443 or the NDVI decline is not caused by drought. It should be noted that in the real world, Scenario 3
444 may develop into overshoot drought for certain ecosystems. Our objective here is not to verify the
445 performance of the simple model, but to test the effectiveness of the overshoot identification
446 algorithm based on these synthetic data. Our overshoot identification algorithm correctly identifies
447 the overshoot drought in Scenario 1, and correctly identifies the other scenarios as non-overshoot
448 droughts (Supplementary Fig. S17-19). This experiment demonstrates the effectiveness of our
449 algorithm in identifying the overshoot drought. More detailed information is provided in
450 Supplementary Text S4 and Fig. S17-19.

451

452 **Machine learning models to predict the numbers and impacts of overshoot drought events**

453 We use two random forest algorithms with 13 independent variables each to predict the fraction
454 of drought events related to overshoot and the fraction of lagged effect to the total impacts of
455 overshoot droughts, respectively. The 13 shared variables include climate variables, e.g., mean
456 annual temperature (MAT), interannual variation of MAT, mean precipitation, interannual
457 variation of precipitation, asynchronicity between the months of maximum temperature and
458 precipitation. Ecosystem vegetation characteristics, including biodiversity, i.e., number of native
459 species within a grid (Data available from <http://ecotope.org/anthromes/biodiversity/plants/data/>),
460 mean NDVI, interannual variability of NDVI, length of the growing season (from MODIS derived
461 phenology, data available from <https://vip.arizona.edu/>) and hydroclimate indicators, e.g., aridity
462 index (precipitation over potential evapotranspiration), terrestrial water decay time from GRACE

463 (GRACE τ)⁴³ and soil characteristic, e.g., the fraction of clay calculated as the average of clay
464 fraction for the top layer and the lower layer (data from RegridDED Harmonized World Soil
465 Database v1.2, <https://daac.ornl.gov/SOILS/guides/HWSD.html>). The climate variables are all
466 calculated using the CRU dataset during 1982-2015. As the contribution of one precipitation event
467 to the total water storage decays exponentially over time, GRACE τ describes the time length (in
468 days) when the contribution decreases to $1/e$ ($\approx 37\%$) of its initial value. Drought recovery time⁴⁴
469 and elevation are also tested in the model, but both showed very little contribution (<0.001) and
470 are not used in the analysis. In addition to these two random forest models, we also build two other
471 models which directly predict the overshoot numbers and lagged impacts, with the total drought
472 number and total NDVI decline during overshoot droughts as additional independent variables,
473 respectively.

474

475 The random forest is a machine learning algorithm consisting of multiple regression trees using
476 bootstrapped samples. In this study, each random forest consists of 500 regression trees with a leaf
477 node size no smaller than 5. A regression tree recursively splits samples into two categories (i.e.,
478 branches) using a binary rule at each step (for one independent variable), minimizing the variance
479 within each branch. Based on the number of times each variable is used for the split, the variable
480 importance metric can be calculated using the fitted random forest and the entire dataset. A larger
481 number of splits indicates the variable is more important for the prediction of the response variable.
482 The variable importance factors are normalized to unity (summation equals to one) for the two
483 random forests.

484

485 The response function of fraction of overshoot drought numbers or impacts to each individual
486 factor is shown as a partial dependent plot (PDP). The PDP calculates the predicted mean response
487 of the target variable (e.g., number or impact of overshoot drought) to one independent variable
488 (e.g., biodiversity), allowing other variables to change in their domain. In practice, it can be
489 calculated as:

$$490 \quad \hat{f}_{x_s}(x_s) = \frac{1}{n} \sum_{i=1}^n \hat{f}(x_s, x_c^{(i)})$$

491 where \hat{f}_{x_s} is partial dependent function with respect to variable x_s , x_c are the other variables used
492 in the random forest. The superscript “(i)” indicates one incident in the dataset.

493

494 **Data Availability**

495 The NDVI 3g v1 dataset is available at <https://ecocast.arc.nasa.gov/data/pub/gimms/>, the CRU
496 climate dataset is available at <https://crudata.uea.ac.uk/cru/data/hrg/>, the GPCP precipitation data
497 is available at <https://www.dwd.de/EN/ourservices/gpcp/gpcp.html>, phenology metrics derived
498 from MODIS are available at https://vip.arizona.edu/viplab_data_explorer.php, the SPEI dataset
499 is available at <https://spei.csic.es/database.html>, the ERA5 soil moisture data is available at
500 <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-means>, the
501 SoMo.ml soil moisture data is from <https://www.bgc-jena.mpg.de/geodb/projects/Home.php>

502

503 **Code Availability**

504 The codes for the dynamic linear model and overshoot identification are available at
505 <https://github.com/zhangyaonju/Overshoot/>.

506

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- 604

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612

613 **Author Contributions**

614 YZ and TFK conceived the idea, YZ designed the study, performed the analysis and wrote the
615 manuscript. YZ, TFK and SZ discussed and commented on the results and the manuscript.

616

617 **Competing Interests**

618 The authors declare no competing interests.

619

620 **Additional Information**

621 Supplementary Information is available for this paper.

622 Correspondence and requests for materials should be addressed to Y.Z. or T.F.K.

623

624 **Figure Legends**

625 **Fig. 1 | Spatial patterns of the number and impact of overshoot drought events. a,b** number
626 of droughts and number of overshoot droughts during 1981 to 2015. **c** latitudinal distribution of
627 the fraction of drought related to overshoot. The black line indicates the total overshoot fraction,
628 colored lines indicate the fraction of overshoot happening at sub-seasonal to interannual scales
629 (see Methods). **d** summation of NDVI declines for the overshoot drought events. **e** NDVI declines
630 caused by the lagged adverse effect (direct overshoot impact). **f** fraction of total overshoot
631 contribution to the NDVI decline (black) and fraction for each overshoot component (colored
632 lines). The drought events are identified by a combination of climatological drought severity and
633 their impact on vegetation (see Methods).

634

635 **Fig. 2 | Response functions for the fraction of drought events related to overshoot and**
636 **fraction of drought impact attributed to overshoot. a-m,** Response functions obtained from the
637 random forest models. The left axis shows the fraction of drought events related to overshoot and
638 the right axis shows the fraction of lagged adverse impact to total NDVI decline for overshoot
639 droughts (see Methods). The numbers in the top-left and top-right corners indicate the order of
640 importance for predicting the fraction of occurrence and lagged impacts of overshoot drought,
641 respectively. **n-o** normalized variable importance for predicting occurrence fraction (**n**) and impact

642 fraction (**o**). MAT: mean annual temperature; IAV: inter-annual variability; LGS: length of
643 growing season; GRACE τ : terrestrial water decay time from GRACE. Biodiversity is assessed by
644 the number of native species within each grid cell (see Methods). Types of major land cover types
645 in **e** are evergreen needleleaf forest (ENF), evergreen broadleaf forest (EBF), deciduous needleleaf
646 forest (DNF), deciduous broadleaf forest (DBF), mixed forest (MF), close shrubland (CSH), open
647 shrubland (OSH), woody savannas (WSA), savannas (SAV), grassland (GRA), wetland (WET)
648 and cropland (CRO).

649

650 **Fig. 3 | Temporal distribution and temperature differences for overshoot droughts. a** Months
651 when overshoot droughts are most likely to start. **b-e** temporal distribution of overshoot (red) and
652 non-overshoot (blue) droughts for four aridity regions using peak growing season as a reference
653 (**b** arid, **c** semi-arid, **d** dry sub-humid, **e** humid). Negative values indicate the droughts happen
654 before the growing season peaks. **f-i** temperature differences for overshoot droughts for four aridity
655 regions. Red bars indicate the mean climatological temperature difference for overshoot (T_{OD}) and
656 non-overshoot (T_{NOD}) drought events. Climatological temperature for each month is calculated
657 during 1981-2015 for each pixel. Orange bars indicate the mean temperature anomaly for
658 overshoot droughts after removing the climatological mean (ΔT_{OD}). Error bars indicate the 95%
659 confidence interval from bootstrap analysis ($n=2000$). An asterisk above the bar indicates the
660 temperature difference is significantly different from zero ($P<0.0001$, paired two-sided t-test).

661

662 **Fig. 4 | A comparison of the development speed of drought impacts on vegetation between**
663 **overshoot and non-overshoot drought events. a** Differences between mean development speed
664 of drought impacts for all overshoot and non-overshoot drought events. The inset in **a** shows the

665 histogram of these differences, with the dashed vertical line showing the mean value. The
666 development speed for each drought event is calculated as the median value of the NDVI change
667 rate during the drought development period. **b-g** changes in standardized NDVI anomalies during
668 drought development periods for six regions across the globe. The de-seasonalized detrended
669 NDVI anomalies are standardized using their standard deviations so that changes can be compared
670 across pixels in each region. Month 0 corresponds to the start of the drought event (first negative
671 NDVI anomaly). Subsets in each region show the comparison between NDVI decline speed during
672 the drought development stage for overshoot (red) and non-overshoot (blue) drought events (see
673 Methods). The mean and s.d. are calculated from all drought events from all pixels within the
674 region.

675

676 **Fig. 5. NDVI changes due to overshoot. a** The spatial pattern of different types of overshoot
677 effects on modulating drought impact based on results from three nested models. White area
678 indicates insufficient samples for model fitting (see Methods). **b** Average NDVI changes due to
679 overshoot. These changes are predicted by the nested models together with the mean standardized
680 precipitation evapotranspiration index (SPEI) values for all overshoot droughts. The widths of the
681 bars indicate the areal fractions for each type. Error bars indicate the s.d. of spatial variations. The
682 subplots in **b** show five types of responses of how overshoot modifies the NDVI and SPEI
683 relationship. These five types of responses differ in their regression intercepts and slopes for
684 overshoot and non-overshoot droughts. The x-axis indicates the drought severity (minimum SPEI
685 values during drought) and the y-axis indicates the drought impact (minimum standardized NDVI).
686 The direction of arrows indicates a decrease for both (stronger drought severity and impact).

687

688 **Figure Legends for Extended Data**

689 **Extended Data Fig. 1. Framework of DLM.** The DLM is composed of five terms, i.e.,
690 temperature component, precipitation component, direct and lagged vegetation components from
691 previous months, trend component, and seasonal component. Numbers in the dashed box indicate
692 the previous months used to calculate anomalies for NDVI, precipitation and temperature. The
693 three seasonal components are harmonic functions with different frequencies.

694

695 **Extended Data Fig. 2. An example of DLM decomposition of the NDVI time series, and the**
696 **identification of an overshoot drought event. a** Satellite retrieved time series of NDVI (black)
697 and DLM predicted NDVI (red) in a grassland at Kansas, USA (latitude = 38.05°N, longitude =
698 96.44° W). **b-k**, Zoom-in of comparison of DLM components during 2011-2012. **b** NDVI
699 anomalies (NDVI minus long-term mean). **c** Trend component in DLM. **d** Three seasonal
700 components. **e** de-seasonalized detrended NDVI observation (black, NDVI observation – trend
701 and seasonal components) and predicted by the DLM (red, summation of precipitation,
702 temperature components and previous month NDVI components). Pink shade indicates drought
703 period. **f** Precipitation component (solid red line, left axis) and coefficient for precipitation (dashed
704 blue line, right axis). **g** Temperature component (solid red line, left axis) and coefficient for
705 temperature (dashed blue line, right axis). **h-l** Lagged effects (left) and the corresponding
706 coefficients (right) from previous month (**h**), 2-3 months (sub-seasonal) (**i**), 4-6 months (seasonal)
707 (**j**), 7-12 months (intra-annual) (**k**), 13-24 months (inter-annual) (**l**). Orange shades indicates the
708 overshoot periods, with hatched ones indicate the overshoot components identified by our
709 algorithm. Shaded areas around the blue dashed lines represent the 90% confidence interval. Take
710 this 2012 summer drought event as an example, among the four lagged effects, previous month 2-

711 3 shows a strong negative sensitivity and a negative contribution during the drought period,
712 therefore it is considered as an overshoot component, its contribution also dominates all the lagged
713 effect during the drought, this drought event is therefore considered as an overshoot drought event.

714

715 **Extended Data Fig. 3. Contribution of each component to overshoot number and impact. a-**
716 **d** Numbers of overshoot component at different time scales. **e-h** Impact of overshoot component
717 at different time scales. Sub-seasonal indicates lagged effect from previous 2-3 months, seasonal
718 indicates 4-6 months, intra-annual for 7-12 and inter-annual for 13-24 months.

719

720 **Extended Data Fig. 4. Dominant overshoot component along growing season length. a**
721 Average number of overshoot component along growing season length. **b** Average fraction of
722 overshoot component numbers to drought numbers along growing season length.

723

724 **Extended Data Fig. 5. Difference in temperature for overshoot droughts. a** Temperature
725 differences between overshoot and non-overshoot droughts with the climatological means. **b**
726 Average temperature anomalies relative to the climatological means for overshoot droughts. Insets
727 show the histograms of the anomalies.

728

729 **Extended Data Fig. 6. Comparisons of the development speed of drought impact between**
730 **overshoot and non-overshoot drought events. a** The decline speed is calculated as the 1st
731 quantile value of the NDVI changes during the start of the decline to the minimum of the de-
732 seasonalized detrended NDVI anomalies for each drought event. **b** Same as **a**, but using the change

733 of NDVI at the zero-crossing date based on the de-seasonalized detrended NDVI anomalies. Insets
734 show the histogram of the development speed.

735

736 **Extended Data Fig. 7. Differences in soil moisture declining speed between overshoot and**
737 **non-overshoot drought events. a** Speed differences from ERA5 reanalysis soil moisture during
738 1981-2015. **b** Speed differences from a machine learning based soil moisture dataset (SoMo.ml)
739 during 2000-2018. For ERA5, we used overshoot droughts derived from GIMMS NDVI (Fig. 1);
740 for SoMo.ml, we used overshoot droughts derived from MODIS NDVI (Supplementary Fig. S12).
741 Both soil moisture datasets were de-seasonalized and detrended first so that we only focus on the
742 soil moisture anomalies. Soil moisture were integrated for top 1m for ERA5 and 0.5m for SoMo.ml.
743 The pixel-level comparisons were only conducted when at least two overshoot and two non-
744 overshoot drought events happened during the study period. The insets show the histogram of the
745 differences, with negative values indicating average soil moisture declining speed is greater (more
746 negative) for overshoot drought than non-overshoot drought. Units are in $\text{m}^3 \text{m}^{-3} \text{mon}^{-1}$.

747

748 **Extended Data Fig. 8. Comparisons between the drought development time and drought**
749 **lengths. a** average drought development time for overshoot drought event (in months). **b**
750 Differences in drought development time between overshoot and non-overshoot droughts (in
751 months). Drought development time is defined as the monotonical decrease period from local
752 maximum to local minimum in the de-seasonalized detrended NDVI anomalies. Inset in **b** show
753 the histogram of the differences.

754

755 **Extended Data Fig. 9. Comparisons of drought severity and impact between overshoot and**
756 **non-overshoot droughts. a** Differences in minimum de-seasonalized detrended NDVI between
757 overshoot and non-overshoot drought events. **c** Differences in minimum 3-month SPEI anomalies
758 between overshoot and non-overshoot drought events. **b** and **d**, similar as **a** and **c**, but for
759 differences of integrated sum of NDVI and SPEI during drought. Overshoot droughts, compared
760 to the non-overshoot ones, usually have weaker drought stress (bottom panel), but relatively
761 stronger impact on vegetation (upper panel). Insets show the differences in anomalies.

762

763 **Extended Data Fig. 10. Comparison of the coefficients of the nested models that predict**
764 **drought impact as a function of drought severity and overshoot occurrence. a**, spatial pattern
765 of best model (see Methods). **b-d**, coefficients for the model that overshoot only affects intercept.
766 **e-h**, coefficients for the model that overshoot affects both intercept and regression slope between
767 NDVI_z and SPEI. Insets show the histogram of the coefficients. Dotted areas indicate that the
768 coefficient is significant at $p < 0.05$.

769