Exacerbated drought impacts on global ecosystems due to structural overshoot

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

Droughts have a large impact on global terrestrial ecosystems and the associated carbon and water cycles1–4. The impact of drought is dependent not only on the direct effects of concurrent climate anomalies5–8 but also on the ecosystem state, which itself is conditioned by antecedent climate4. For example, a period that is favourable to growth but followed by a water deficit can first stimulate biomass accumulation and, as a result, further deplete soil moisture and increase drought risks. This sequence of events represents a class of state dynamics known as structural overshoot9, where an ecosystem temporarily exceeds the time-varying, climatologically defined baseline carrying capacity and in the process depletes potentially limiting water resources. Several previous studies examined the lagged impact of structural overshoot for specific drought events and regions4,10,11. Understanding of the global occurrence and impact of structural overshoot is limited, however, as ecosystem states are conditioned across multiple different timescales and both the timescales of importance and the ecosystem states change over time. This lack of a global understanding of overshoot constitutes a large uncertainty in understanding drought development and its impacts on vegetation dynamics as well as the global carbon and water cycles.

Here, we use a Bayesian dynamic linear model (DLM) approach12, in combination with long-term (1981–2015) satellite observations, high-resolution climate data and a random forest analysis, to characterize droughts related to structural overshoot (referred to throughout as overshoot droughts) across global ecosystems and examine their impact on terrestrial vegetation–water relations (Extended Data Figs. 1 and 2; Methods). In this study, we characterize drought events using a combination of climatological drought index and associated vegetation greeness decline represented by normalized difference vegetation index (NDVI)13; Methods). While structural overshoot has been examined in the context of regional forest mortality9, here we consider a broader range of global ecosystems and focus on the negative lagged impacts on vegetation (Methods). The DLM allows for the decomposition of satellite-retrieved NDVI time series, into multiple components (trend, seasonal and deseasonalized and detrended anomalies) through a Kalman filtering process (Methods). The anomaly components consist of the direct drought stress, temperature and direct and lagged effects from past vegetation anomalies at different timescales (subseasonal, seasonal, intra-annual and interannual). This approach allows for the separation of the timescales of importance for all drought events globally, which enables us to robustly identify and characterize the role of structural overshoot in the timing, speed, frequency and impact of drought (Methods; Supplementary Text 1–4).

Spatial patterns of overshoot droughts

Our approach quantifies the spatial distribution of the number of droughts and those related to structural overshoot during 1981–2015 (Fig. 1a,b). Globally, 11.2% of the drought events are overshoot related and lagged adverse effects explain 34.7% of the NDVI declines for these overshoot drought events. The number of overshoot droughts generally follows the spatial distribution of droughts ($r=0.45$, $P<0.001$, t-test), with exceptions in southern central United States, northeast Brazil and Australia, where overshoot occurrence relative to drought numbers is low. Spatial autocorrelation does not show strong influence on this covariation and is therefore not considered further in our analysis (Supplementary Text 5 and Supplementary Fig. 2). The fraction of drought events related to overshoot shows a clear latitudinal pattern, with a decreasing trend from north to south (Fig. 1c and Supplementary Fig. 3). Overshoot droughts are influenced by lagged adverse effects at
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regions such as boreal ecosystems in Alaska and Siberia and agro-
impact on NDVI decline (51.8%), which also dominates hotspot
adverse effects from the subseasonal scale also have the largest
temperature is the primary limiting factor for both vegetation phe-
(Fig. 2a,h). In cold regions (mean annual temperature, MAT,<0 °C),
temperature stress, in comparison to water stress, can lead to
exceedance of climatologically defined ecosystem carrying capac-
ally stressed environments, usually with a shorter growing season
(Overshoot droughts are more prevalent in stressed or season-
have a greater proportional impact19. Vegetation coverage, repre-
weaker drought resistance and thus lagged adverse effects tend to
is favourable and soil water depletion at similar rooting depths18).
behaviour (for example, expansive growth when the environment
shoot droughts decrease when the number of native species is
500)
A positive temperature anomaly in the early growing season exponen-
tially increases water consumption18, potentially leading to
higher drought risk and stronger lagged effect. In comparison, mean
annual precipitation plays a less important role. This is probably due
to the fact that soil water is mostly low and has limited buffering
capacity in dry regions; ecosystems are therefore more responsive to
concurrent precipitation anomalies and relatively less dependent on
the lagged effect17. As expected, the number and impact of overshoot
drought events also increases with larger interannual variations of
MAT but much less with precipitation (Fig. 2b,f). Increases in cli-
mate variability not only increase the chances of a more favourable
environment for plant growth in earlier periods but also induce more
frequent extreme heat and dry anomalies, leading to water deficit and
potential drought.

Ecosystem biodiversity also plays a critical role in regulating
overshoot drought occurrence. The number and impact of over-
shoot droughts decrease when the number of native species is >500
(Fig. 2d). Low biodiversity is associated with synchronous plant
behaviour (for example, expansive growth when the environment
is favourable and soil water depletion at similar rooting depths19).
In addition, ecosystems with low biodiversity are expected to have
weaker drought resistance and thus lagged adverse effects tend to
have a greater proportional impact19. Vegetation coverage, repre-
sented by mean annual NDVI, also positively affects the number
of overshoot drought events (Fig. 2g). Higher vegetation coverage
increases the plants’ role in linking the energy and water fluxes
between soils and the atmosphere20. Anomalies in high vegetation
coverage ecosystems would therefore have a greater impact on soil
water and are more likely to induce a lagged adverse effect. Land
cover type also plays an important role, with a higher number and
impact of overshoot drought events for boreal forest and woody
savannas (Fig. 2e).

**Fig. 1 | Spatial patterns of the number and impact of overshoot drought events.** a, Number of droughts during 1981–2015. b, Number of overshoot droughts during the same period. c, Latitude distribution of the fraction of drought related to overshoot. The black line indicates the total overshoot fraction, coloured lines indicate the fraction of overshoot happening at subseasonal to interannual scales (Methods). d, Summation of NDVI declines for the overshoot drought events. e, NDVI declines caused by the lagged adverse effect (direct overshoot impact). f, Fraction of total overshoot contribution to the NDVI decline (black) and fraction for each overshoot component (coloured lines). The drought events are identified by a combination of climatological drought severity and their impact on vegetation (Methods).

different timescales (Extended Data Fig. 3), with a strong depend-
dence on growing season length (Extended Data Fig. 4). The sub-
seasonal scale overshoot component contributes most to the global
overshoot events, especially in northern high latitudes18. Lagged
adverse effects from the subseasonal scale also have the largest
impact on NDVI decline (51.8%), which also dominates hotspot
regions such as boreal ecosystems in Alaska and Siberia and agro-
ecosystems in North China Plain and northern India (Fig. 1d,e and
Extended Data Fig. 3).

**Controlling factors and underlying mechanisms**

To understand which factors contribute to the number and impact
of overshoot droughts, we built random forest models using vari-
ous climate variables and ecosystem characteristics to predict the
spatial pattern of the fraction of drought related to overshoot
and the fraction of lagged adverse effects to total drought impact
(Methods). The resulting models can explain 63.9 and 50.5% of the
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In contrast, soil characteristics (clay fraction), terrestrial water decay time estimated from Gravity Recovery and Climate Experiment satellites (GRACEℓ; Methods) and asynchrony between peak temperature and precipitation show little role in determining the number and impact of overshoot drought events. We also test the robustness of these results by predicting the absolute overshoot drought number and lagged effect instead of their fractions with two other random forest models and find similar environmental dependences (Methods; Supplementary Fig. 4).

**Overshoot and compound drought and heat**

We further analyse the temporal occurrence of overshoot droughts. In the northern mid- to high-latitudes (>30°N), 51.2% of overshoot drought events happen in July and August (Fig. 3a). For the Southern Hemisphere, two peaks can be observed in March and September, which is probably due to the double growing season experienced in many water-limited regions. Similar patterns can also be observed in parts of dry Mediterranean climate regions in the Northern Hemisphere, where overshoot drought may happen in either peak growing season. We also compare the start date for overshoot droughts and non-overshoot droughts. To make these dates comparable across space, they are normalized by the peak growing season and the results are summarized in four aridity regions (Fig. 3b–e). For dryland regions, non-overshoot droughts are more likely to happen before the peak growing season, while overshoot droughts are more likely to happen in the mid-to-late growing season (Fig. 3b,c). These significant differences in drought timing (P < 0.0001, paired two-sided t-test) also suggest that overshoot droughts are more likely to happen before the peak growing season, while overshoot droughts are more likely to happen in the mid-to-late growing season (Fig. 3b,c).
droughts are more likely to happen in warmer months, especially for semi-arid and dry subhumid regions (Fig. 3f–i and Extended Data Fig. 5a). Considering the positive temperature anomalies during the drought period, overshoot droughts tend to have higher risk of extreme temperature. This compound drought and heat can be detrimental to ecosystem functioning and related ecosystem services, particularly for the mid-latitude semi-arid to dry subhumid regions21–23, which are also major crop production areas and densely populated.

Overshoot and the development speed of drought impacts

Globally, overshoot droughts are associated with a faster NDVI decline than non-overshoot droughts ($P < 0.0001$, paired two-sided t-test) (Fig. 4). Similar patterns can also be found if comparing the maximum NDVI decrease speed or the NDVI changes at the zero-crossing month (Extended Data Fig. 6). This faster decrease in NDVI is often accompanied with larger differences in NDVI anomalies between the start and end of the drought development period (Fig. 4b–g). Using soil moisture data from both ERA5 reanalysis24 and a machine learning approach33, we also find faster soil moisture decline for overshoot droughts than for non-overshoot droughts ($P < 0.0001$, paired two-sided t-test) (Extended Data Fig. 7).

However, the differences in soil moisture changes are much smaller than the differences in vegetation declines ($P < 0.0001$, unpaired two-sided t-test), potentially because the interannual variations of vegetation are not used as a forcing in these datasets and their effects on soil moisture may thus be underestimated.

Due to the rapid onset and intensification of vegetation deterioration, most overshoot droughts we identify can also be classified as flash droughts26,27. Flash droughts occur most frequently in mid-latitude semi-arid or dry subhumid regions where overshoot impacts are dominated by the subseasonal and seasonal lagged effects (Extended Data Fig. 3). Most overshoot droughts develop very quickly (mostly 2–3 months) and are on average 1–2 months shorter than non-overshoot droughts in these semi-arid regions (Extended Data Fig. 8).

In addition, overshoot droughts usually lead to stronger drought impacts for dry subhumid and humid regions, as shown by a more negative NDVI anomaly compared to the standardized precipitation evapotranspiration index (SPEI) anomaly (Extended Data Fig. 9). SPEI is a widely used drought severity indicator which calculates the standardized surface water balance anomaly from meteorological variables. To understand how overshoot modulates the drought severity (assessed by minimum SPEI) and impact
Fig. 4 | A comparison of the development speed of drought impacts on vegetation between overshoot and non-overshoot drought events. a. Differences between mean development speed of drought impacts for all overshoot and non-overshoot drought events. The inset in a shows the histogram of these differences, with the dashed vertical line showing the mean value. The development speed for each drought event is calculated as the median value of the NDVI change rate during the drought development period. b–g. Changes in standardized NDVI anomalies during drought development periods for six regions across the globe. b, North Alaska. c, Eastern United States. d. Southern Brazil. e, Southwestern Africa. f, Northern India. g, Central Siberia. The deseasonalized detrended NDVI anomalies are standardized using their standard deviations so that changes can be compared across pixels in each region. Month 0 corresponds to the start of the drought event (first negative NDVI anomaly). Insets in each region show the comparison between NDVI decline speed during the drought development stage for overshoot (red) and non-overshoot (blue) drought events (Methods). The mean and s.d. are calculated from all drought events within the region.

(assessed by minimum of standardized NDVI, NDVL) relationship, we build three nested linear models to predict NDVI, anomalies from SPEI values during droughts. The first model does not consider overshoot effect. The second considers the effect on intercepts only and the third considers the effect on both the regression slopes and intercepts (Methods; Extended Data Fig. 10). The results from this model comparison can be summarized into five types of severity-impact responses (Methods; Fig. 5b). For about a quarter of the area where the three models are evaluated, overshoot exacerbates drought impact to the same degree across different drought severities (Type 1 in Fig. 5). The nested models predict an additional NDVI, decline of \(-0.58 \pm 0.30\). In another quarter of area, overshoot leads to stronger impact when drought severity is low, causing a decrease of NDVI, by \(-0.07 \pm 0.28\) (Type 2 in Fig. 5). By contrast, only 3% of area indicates overshoot has stronger impact when drought severity is high, with an additional NDVI, decline by \(-0.27 \pm 0.24\) (Type 3 in Fig. 5). Overshoot alleviates the drought impact for only 4% of the area (Type 4 in Fig. 5). This may be due to a mismatch in timing when drought or overshoot impact reach their maximum.

Our analysis, based on a dynamic statistical learning approach applied to long-term satellite vegetation records, provides a global understanding of the role of vegetation structural overshoot in the timing, speed and impact of drought events. Overshoot droughts are found to develop faster and be more likely to compound with extreme heat than are non-overshoot droughts, exacerbating the drought impact on ecosystem function and the associated societal services. Overshoot droughts are also expected to be associated with increased competition, changes in species composition and functional groups. It is not possible, however, to analyse these ecological processes at global scales in our study and they therefore warrant further analysis. Soil water balance may be the key to link the lagged adverse effects but land–atmosphere feedbacks\(^{11,19}\) and other processes such as plant phenology\(^{30}\) and fire disturbance play potentially important roles. Current drought indices, including those relying on potential evapotranspiration, do not consider vegetation status in calculating the water balance and may therefore underestimate drought severity when structural overshoot happens. Global climate change can promote faster vegetation growth\(^{32}\) and soil water depletion\(^{33}\), together with more frequent and severe climate extremes, potentially increasing the overshoot drought occurrence and impact. Continuous satellite monitoring and improved model simulation are needed to help better understand the changes of overshoot and improve the prediction of future drought impacts.

**Methods**

**GIMMS NDVI and climate datasets.** We use the NDVI from Global Inventory Monitoring and Modeling System (GIMMS) 3gvi (1981–2015; ref. \(^{13}\)) which provides long-term records for vegetation activity. NDVI is a remotely sensed indicator based on the unique spectral characteristics of vegetation and has been demonstrated to be strongly related to ecosystem leaf area index and photosynthetic capacity\(^{14,15}\). It can therefore represent the aggregated ecosystem response to climatic anomalies and drought stress. This dataset is first quality checked and aggregated to monthly 0.5°×0.5° resolution to match the resolution of other datasets and to reduce the uncertainty. In many northern regions, the quality flags are not always effective, especially when mixed snow pixels exist. Since the DLM is sensitive to these deseasonalized anomalies and drought and water limitations are not likely to happen during these cold and snow-covered periods, we therefore use an additional temperature threshold to filter out these potential contaminated pixels: if the mean air temperature for a specific month is <0°C, the land surface may be covered by snow and the corresponding NDVI is set to NA.

We use both precipitation and temperature as environmental variables in the DLM. The precipitation dataset is from the Global Precipitation Climatology Centre (GPCC)\(^{17}\). This dataset provides monthly precipitation at a 0.5°×0.5° spatial resolution. The dataset is generated using a spatial statistical method based on
The multivariate DLM is a type of linear model that we use a Kalman filter to get the posterior estimates of $y$ to get the posterior estimates of $\theta$. In this study, we focus on the posterior estimates of the regression coefficients for the previous months' NDVI, named DLM sensitivities. These sensitivities, together with their corresponding NDVI anomalies (contributions to the predicted current month NDVI from each of the previous months' NDVI, for example, $\delta$NDVI$_{-24}$) were used to identify overshoot droughts. Since the DLM uses a Kalman filter at each time step, to get a reliable prediction of the coefficient, especially in the early study period, we use a 'spin-up' period by recycling the first 5 years (1981–1986) of satellite NDVI and climate observations two times before the start of the dataset. It should be noted that although the model is a class of 'linear models', its sensitivities change through time and thus can capture temporal nonlinearity. A detailed description of this method can be found in Supplementary Text 1. In addition to this 'default model' setup which considers both temperature and precipitation in the regression component, we also test a reduced model which does not consider temperature and an 'extended model' that considers precipitation, temperature and radiation. A detailed description of these experimental setups, together with other sensitivity analyses, can be found in Supplementary Text 2.

Drought and overshoot identification. We use a combination of SPEI and NDVI together with outputs from the DLM to identify drought events. Both indices are directly calculated from observations and represent the climatological drought severity and the drought impact on vegetation, respectively. After the NDVI time series for each pixel is decomposed by the DLM, we identify all negative anomalies from the deseasonalized and detrended NDVI (original NDVI minus trend and seasonal components obtained from DLM decomposition). For each consecutive negative NDVI anomaly time window, a minimum value is first retrieved. A drought starts when the NDVI anomaly turns negative and ends when the NDVI anomaly recovers $>70\%$ of the minimum value. Three criteria need to be met to be considered as a drought event: (1) drought should be at least 2 months long and the minimum NDVI anomaly should be smaller (more negative) than 10% of the mean NDVI to exclude events due to random noise in NDVI; (2) the average SPEI during the corresponding period is below $-0.5$. It should be noted that we used a relaxed threshold for SPEI ($-0.5$ compared to commonly used $-1$), since overshoot droughts may happen with only moderate precipitation deficit ($-0.5$) the temperature component during the drought period should be greater than the precipitation component (less negative) or the temperature sensitivity (coefficient at STemp) should be negative. This is to exclude the NDVI decline due to low temperature rather than low soil water.

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

In practice, after drought events are identified for each pixel, we calculate the average NDVI anomaly and DLM sensitivity during each drought period for each of the four previous-month NDVI components, that is, previous 2–3 months, previous 4–6 months, previous 7–12 months and previous 13–24 months (Extended Data Fig. 1). For each drought event, if any of the four previous-month NDVI components have a positive anomaly associated with a significantly negative (CI $= 0.9$) sensitivity coefficient (that is, the total contribution (the product of NDVI anomaly and sensitivity) to the prediction of current NDVI is negative) this NDVI component is regarded as an overshoot component. For a given drought event, if the summation of all overshoot component contributions is greater than the non-overshoot contributions by absolute value and the minimum of the overshoot component is $< -0.01$, this drought event is considered as an overshoot drought event. Since we use several arbitrary thresholds in the drought and overshoot drought identification, we also test the uncertainties caused by the model structure and thresholds chosen. The results show that different models and thresholds can affect the absolute number of droughts and overshoot droughts; however, the spatial patterns are quite similar and the fraction of overshoot drought numbers
to total drought numbers is conservative, ranging from 9.93 to 18.49%, with a median value of 11.22%. Detailed information is provided in Supplementary Text 2, Supplementary Table 1 and Supplementary Figs. 5–11. In addition to GIMMS NDVI, we also use NDVI from the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD13C2 and identify overshoot during 2000–2018. The resulting spatial patterns are similar with those obtained using GIMMS NDVI (Supplementary Fig. 12).

To understand the differences in development speed of drought impact between overshoot and non-overshoot drought, we first define a drought development period which begins with the monotonical decrease of the deseasonalized detrended NDVI anomalies and ends when it reaches its minimum within a drought event. Within each drought development period, we first calculate the speed of changes as the differences in deseasonalized detrended NDVI anomalies between months. We compare three metrics to characterize the development speed of drought impact: the speed of changes at its maximum (75th percentile), median (50th percentile) and at the zero-crossing month (that is, when the NDVI anomalies shift from positive to negative).

Timing of overshoot. We identify the starting month for each drought event to examine drought timing. For each pixel, the average starting months for overshoot and non-overshoot drought events are calculated separately. We fit a probability density function (PDF) of the overshoot drought starting date for each pixel and determined the months when the probability reaches its maximum. Since December and January are also nearby months but the PDF cannot be correctly fitted under this condition, we shift the starting months 3, 6 and 9 months and fit three other PDFs. The final starting date is determined by the month that corresponds to the maximum probability across all four PDFs. If the maximum probabilities for the four PDFs are the same, it indicates that the starting dates of overshoot drought do not have any tendency and this pixel is not used. This only happens for a very small proportion of the total area (~0.5%). To make these times comparable across space, we shift the starting month of each drought event by the peak growing season. These differences are then rescaled to −6 to +6 months.

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

$$\text{NDVI} = \alpha \times \text{SPEI} + b$$

(3)

$$\text{NDVI} = \alpha \times \text{SPEI} + C \times \text{overshoot} + c$$

(4)

$$\text{NDVI} = (a + c \times \text{overshoot}) \times \text{SPEI} + b \times \text{overshoot} + d$$

(5)

The first model (null model) only considers water deficit as indicated by 3-month SPEI. The second model assumes that when overshoot happens, it will change the intercept of the regression. The third model assumes that when overshoot happens, both the intercept and the sensitivity of SPEI will change. Since there is a limited number of overshoot drought events for each pixel, we evaluate these three models on 2.5°×2.5° windows, so that each window has at least ten overshoot droughts and ten non-overshoot droughts during the study period. To make NDVI declines comparable within each window, the NDVI declines are standardized by the standard deviation of deseasonalized detrended anomalies (NDVI, z-score). The best model is selected on the basis of an analysis of variance comparison; second and third models are only selected when they are significantly better than the first model (P<0.1).

On the basis of the comparison of these three models, we categorize overshoot impact into five groups (Fig. 5). (1) Overshoot has no effect on the NDVI–SPEI relationship. This is considered when the first model is chosen. (2) Overshoot decreases the intercept of the NDVI response to SPEI but the NDVI response to SPEI remains the same. This is considered when the second model is chosen and coefficient $b$ is negative. (3) Overshoot decreases the intercept of the NDVI response to SPEI but the sensitivity of NDVI to SPEI is reduced. This is considered when the third model is chosen and both coefficients $b$ and $c$ are negative. (4) Overshoot increases the intercept of the NDVI response to SPEI and the sensitivity of NDVI to SPEI is increased. This is considered when the third model is chosen and both coefficients $b$ and $c$ are positive. (5) Overshoot alleviates the drought impact. This is considered when all other cases happen. To assess the overshoot impact on drought, we predict the effect related to overshoot on the basis of the best model selected and average SPEI values for all overshoot drought events within this 2.5°×2.5° window.

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

1. Twelve months are grouped into six groups, with each group have two consecutive months (for example, January and February, March and April),

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

3. Using this randomized dataset, we again run the DLM model and identified the drought and overshoot drought events for 1981–2015.

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

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

We also test if the lagged effect can be partially retained if we choose larger group sizes. To do so, instead of swapping the NDVI by 2-months group in step (1), we use larger group sizes of 6-months and 24-months during the swap. For example, March to August in 2012 will be moved together to March to August in 1999 (6-month group) or September 2010 to August 2012 will be moved together to September 1982 to August 1984 (24-months group). By using larger groups, partial lagged effects may be retained, for example, the lagged effects at subseasonal scale may be kept using the 6-months group size and the effect at intra-annual scale may be kept if we use 24-months group size.

We find that when using a group size of 2 months, the spatial pattern of drought numbers does not change much, while most of the overshoot droughts are no longer identified. With the increase of the group sizes, more overshoot drought events are identified and the spatial patterns become similar to the one we obtained without randomization. This suggests that the DLM can effectively capture the lagged effect and help identify overshoot drought events. More detailed information is provided in Supplementary Text 3 and Supplementary Figs. 14–16.

Synthetic data experiment. We also generate a synthetic dataset to test if overshoot drought events can be effectively identified using our methodology. To do this, we first build a simple vegetation model that considers both the direct effect of environment and the lagged effect of previous months NDVI through soil water dynamics (Supplementary Text 4). We focus on the 2012 overshoot drought in central United States. Using this simple model, we set up four different scenarios to simulate vegetation dynamics and applied the overshoot identification algorithm used in this study:

1. Control run, spring warming and low summer precipitation
2. No spring warming, low summer precipitation
3. Spring warming, normal summer precipitation
4. Spring warming, abundant summer precipitation but with other disturbances

These four scenarios differ in their environmental drivers and, consequently, NDVI anomalies simulated by the simple model. On the basis of the synthetic data, only scenario (1) is considered as an overshoot drought event, while for the other three, they either do not exhibit a lagged adverse effect or the NDVI decline is not caused by drought. It should be noted that in the real world, scenario (3) may develop into overshoot drought for certain ecosystems. Our objective here is not to verify the performance of the simple model but to test the effectiveness of the overshoot identification algorithm based on these synthetic data. Our overshoot identification algorithm correctly identifies the overshoot drought in scenario (1) and correctly identifies the other scenarios as non-overshoot droughts (Supplementary Figs. 17–19). This experiment demonstrates the effectiveness of our algorithm in identifying the overshoot drought. More detailed information is provided in Supplementary Text 4 and Supplementary Figs. 17–19.

Machine learning models to predict the numbers and impacts of overshoot drought events. We use two random forest algorithms with 13 independent variables each to predict the fraction of drought events related to overshoot and the fraction of lagged effect to the drought event. The 13 shared variables include climate variables: for example, MAT, interannual variation of MAT, mean precipitation, interannual variation of precipitation, synchronicity between the months of maximum temperature and precipitation; ecosystem characteristics, including biodiversity, that is, number of native species within a grid (data available from http://ecotope.org/anthromes/biodiversity/plants/databases/); and NDVI, interannual variability of NDVI, length of the growing season (from MODIS derived phenology, data available from https://vip.arizona.edu/); hydroclimate indicators, for example, aridity index (precipitation over potential evapotranspiration), terrestrial water decay time from GRACE (GRA(C)ER)\textsuperscript{2}; and
of the variable importance factors are normalized to unity (summation equals one) for the two random forests.

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

\[
\hat{f}_i(x_i) = \frac{1}{n} \sum_{i=1}^{n} \hat{f}(x_i|x_i^{(-i)})
\]

where \( \hat{f}_i \) is partial dependent function with respect to individual variable \( x_i \) and \( x_i^{(-i)} \) are the other variables used in the random forest. The superscript \( (\cdot) \) indicates one incident in the dataset.

**Reporting Summary.** Further information on research design is available in the Nature Research Reporting Summary linked to this article.

**Data availability.**

The NDVI 3g dataset is available at http://poles.tpdce.ac.cn/en/data/97752b4-77370-4e5e-a337-3482ca9d38b8/, the CRU dataset is available at https://crudata.uea.ac.uk/cru/data/hrg/; the GPCC precipitation data are available at https://www.dwd.de/EN/ourservices/gpcc/gpcc.html; the soil moisture metrics derived from MODIS are available at https://vip.arizona.edu/viplab_data_explorer.php, the ERA5 soil moisture data are from http://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-means and the SoMo.ml soil moisture data are from https://www.bgc-jena.mpg.de/geodb/projects/Home.php. The source data for the SPEI dataset is available at https://spei.csic.es/database.html, the ERA5 soil moisture and precipitation datasets are from MODIS data. The codes for the DLM and overshoot identification are available at https://github.com/zhangyaojun/Overshoot.

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Author contributions

Y.Z. and T.F.K. conceived the idea. Y.Z. designed the study, performed the analysis and wrote the manuscript. T.F.K. and S.Z. discussed and commented on the results and the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Extended Data Fig. 1 | Framework of DLM. The DLM is composed of five terms, that is, temperature component, precipitation component, direct and lagged vegetation components from previous months, trend component, and seasonal components. Numbers in the dashed box indicate the previous months used to calculate anomalies for NDVI, precipitation and temperature. The three seasonal components are harmonic functions with different frequencies.
Extended Data Fig. 2 | See next page for caption.
Extended Data Fig. 2 | An example of DLM decomposition of the NDVI time series, and the identification of an overshoot drought event. a Satellite-retrieved time series of NDVI (black) and DLM predicted NDVI (red) in a grassland at Kansas, USA (latitude = 38.05°N, longitude = 96.44°W). b–k, Zoom-in comparison of DLM components during 2011–2012. b NDVI anomalies (NDVI minus long-term mean). c Trend component in DLM. d Three seasonal components. e de-seasonalized detrended NDVI observation (black, NDVI observation – trend and seasonal components) and predicted by the DLM (red, summation of precipitation, temperature components and previous-month NDVI components). Pink shade indicates drought period. f Precipitation component (solid red line, left axis) and coefficient for precipitation (dashed blue line, right axis). g Temperature component (solid red line, left axis) and coefficient for temperature (dashed blue line, right axis). h–l Lagged effects (left axis) and the corresponding coefficients (right axis) from previous months (h), 23 months (subseasonal) (i), 4–6 months (seasonal) (j), 7–12 months (intra-annual) (k), 13–24 months (interannual) (l). Orange shades indicate the overshoot periods, with hatched ones indicate the overshoot components identified by our algorithm. Shaded areas around the blue dashed lines represent the 90% confidence interval. Take this 2012 summer drought event as an example, among the four lagged effects, previous-month 2–3 shows a strong negative sensitivity and a negative contribution during the drought period, therefore it is considered as an overshoot component, its contribution also dominates all the lagged effects during the drought, this drought event is therefore considered as an overshoot drought event.
Extended Data Fig. 3 | Contribution of each component to the overshoot number and impact. a–d Numbers of overshoot component at different timescales. e–h Impact of overshoot component at different timescales. Subseasonal indicates lagged effect from previous 2–3 months, seasonal indicates previous 4–6 months, intra-annual for previous 7–12 and interannual for previous 13–24 months.
Extended Data Fig. 4 | The dominant overshoot component along the growing season length. **a** Average number of overshoot component along the growing season length. **b** Average fraction of overshoot component numbers to drought numbers along the growing season length.
Extended Data Fig. 5 | Differences in temperature for the overshoot droughts. **a** Temperature differences between overshoot and non-overshoot droughts with the climatological means. **b** Average temperature anomalies relative to the climatological means for the overshoot droughts. Insets show the histograms of the anomalies.
Extended Data Fig. 6 | Comparisons of the development speed of drought impact between overshoot and non-overshoot drought events. **a** The development speed is calculated as the 1st quantile value of the NDVI changes during the start of the decline to the minimum of the de-seasonalized detrended NDVI anomalies for each drought event. **b** Same as **a**, but using the change of NDVI at the zero-crossing date based on the de-seasonalized detrended NDVI anomalies. Insets show the histogram of the development speed.
Extended Data Fig. 7 | Differences in the soil moisture declining speed between overshoot and non-overshoot drought events. a Speed differences from ERA5 reanalysis soil moisture during 1981–2015. b Speed differences from a machine learning based soil moisture dataset (SoMo.ml) during 2000–2018. For ERA5, we used overshoot droughts derived from GIMMS NDVI (Fig. 1); for SoMo.ml, we used overshoot droughts derived from MODIS NDVI (Supplementary Fig. 12). Both soil moisture datasets were de-seasonalized and detrended first so that we only focus on the soil moisture anomalies. Soil moisture were integrated for top 1m for ERA5 and 0.5m for SoMo.ml. The pixel-level comparisons were only conducted when at least two overshoot and two non-overshoot drought events happened during the study period. The insets show the histogram of the differences, with negative values indicating average soil moisture declining speed is greater (more negative) for overshoot drought than non-overshoot drought. Units are in $m^3 m^{-3} mon^{-1}$. 
Extended Data Fig. 8 | Comparisons between the drought development time and drought lengths. 

**a** Average drought development time for overshoot drought event (in months).

**b** Differences in drought development time between overshoot and non-overshoot droughts (in months). Drought development time is defined as the monotonical decrease period from local maximum to local minimum in the de-seasonalized detrended NDVI anomalies. Inset in **b** shows the histogram of the differences.
Extended Data Fig. 9 | Comparisons of drought severity and impact between overshoot and non-overshoot droughts. **a** Differences in minimum de-seasonalized detrended NDVI between overshoot and non-overshoot drought events. **c** Differences in minimum 3-month SPEI (SPEI3) anomalies between overshoot and non-overshoot drought events. **b** and **d**, similar as **a** and **c**, but for differences of integrated sum of NDVI and SPEI during drought. Overshoot droughts, compared to the non-overshoot ones, usually have weaker drought stress (bottom panel), but relatively stronger impact on vegetation (upper panel). Insets show the histogram of differences in anomalies.
Extended Data Fig. 10 | See next page for caption.
Extended Data Fig. 10 | Comparison of the coefficients of the nested models that predict drought impact as a function of drought severity and overshoot occurrence. a spatial pattern of the best model being selected (Methods). b-d coefficients for the model that overshoot only affects intercept. e-h coefficients for the model that overshoot affects both intercept and regression slope between NDVI, and SPEI. Insets show the histogram of the coefficients. Dotted areas indicate that the coefficient is significant at $P<0.05$. 
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Data collection  No software was used to collect data.

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All studies must disclose on these points even when the disclosure is negative.

| Study description | We used satellite observations, climate datasets and a statistical learning approach to understand the occurrence, timing, development speed, and impact of droughts that are related to structural overshoot. |
|-------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Research sample   | We identified the drought events happened during 1981-2015 and classified them into overshoot drought and non-overshoot drought based on the algorithm we developed. |
| Sampling strategy | We used all drought samples to understand the occurrence, timing, drought development speed, and impact of overshoot drought. Several hotspot regions were selected and showed in detail. |
| Data collection   | All datasets were downloaded using the URLs in the data availability statement in the main text. |
| Timing and spatial scale | The NDVI data used here has a biweekly temporal resolution and 0.083 degree spatial resolution. The precipitation dataset from GPCP, temperature dataset from CRU and radiation from CRU-NCEP have a monthly temporal resolution and 0.5 degree spatial resolution. We also used the SPEI dataset that is based on the CRU climate dataset. All these datasets cover the period from 1981-2015 for the global vegetated land. |
| Data exclusions   | The NDVI dataset may suffer from snow or other data quality issues during winter time, we therefore used air temperature to exclude these potentially biased observations. Details were reported in the Method section. |
| Reproducibility  | Our analyses were based on public satellite and climate products and well-defined methods, the results could be reliably reproduced. |
| Randomization     | We designed a randomization experiment to test the robustness of the dynamic linear model in capturing the lagged effect of vegetation. Details were reported in the Method section. |
| Blinding          | Our study only used existing data, therefore blinding is not relevant to our study. |

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Methods

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- ChiP-seq
- Flow cytometry
- MRI-based neuroimaging