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The forest recovery path after drought dependence on forest type and stock volume

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Abstract
Drought legacy effects of forest ecosystems have been widely observed. However, the influence of forest type and stock volume on its recovery path is poorly understood. In this research, we first used the Standardized Precipitation Evapotranspiration Index to identify a drought event. Then, we applied the normalized difference vegetation index deficit and forest property maps derived from forest inventories to investigate the potential impacts of forest properties on forest recovery paths. The results showed that the legacy effects 1–3 years after a drought event were pervasive, but the forest recovery path was highly dependent on the forest type and forest stock volume. The recovery of forests with low stock volume densities (<60 m³ ha⁻¹) was mostly stronger than that of forests with high stock volume densities (≥60 m³ ha⁻¹) by the second year. Although all forests with different stock volume densities approximately returned to a normal status by the third year, they followed various paths to recovery. Natural coniferous forests in China that have a similar stock volume density (<60 m³ ha⁻¹) took longer to recover than planted coniferous forests and exhibited a lower magnitude of recovery. These findings highlight that drought legacy effects are greater for natural coniferous forests with high stock volume densities, which provides insightful forest management information on how to speed up forest recovery with forest density control and type control.

1. Introduction

There is increasing recognition of the economic, social and environmental benefits of forests. Forests are a source of income, employment, food, timber and medicines, and contribute to soil conservation, carbon sequestration and habitat protection [1–3]. However, the frequency and severity of extreme weather events, such as droughts, are expected to increase [4–6]. Drought events are likely to strongly influence a forest’s structure, function, and the ecosystem services it provides [5, 7], and can cause the death of trees by hydraulic failure and/or carbon starvation [4, 8–12]. Previous studies have demonstrated that the drought-induced forest mortality can cause the vegetation system to go from a net carbon sink to a significant carbon source, creating sizable positive feedback to global warming [4, 5, 11, 13, 14]. Thus, understanding forest drought response characteristics is crucial for forest management, and will contribute to reducing drought risk and slowing global warming.

However, gaining a quantitative understanding of drought effects on forests is challenging because complicated processes and multiple interacting factors are involved [15–19]. For instance, forests are not
only impacted from current droughts, but also from past drought events, known as drought legacy effects [15, 20]. Previous drought events can have substantial legacy impacts on vegetation dynamics that may last for 1–6 years in different research regions, and despite the drought being meteorologically or hydrologically alleviated the observable legacy effects include reduced growth and incomplete forest recovery, and changes in vegetation responses to current water conditions [21, 22]. Thus, revealing the legacy effects of drought on forests will help broaden our understanding of the mechanisms determining forest responses to drought.

The drought legacy effect is defined by a departure (unitless) of the observed vegetation growth from the predicted vegetation growth in a period after a drought event, and is often used in recent studies that utilized remote sensing data [22–24]. Those studies found that the duration and magnitude of drought legacy effects on forests is contingent on site characteristics (i.e. elevation [23], water table depth [25] and water balance [26]), drought characteristics (i.e. severity and seasonal timing) [16, 18], species composition, and the forest’s functional properties [20, 22, 26]. Although some progress in understanding drought legacy effects has been achieved, it remains unexplored how forest properties, such as stock volume and forest type (i.e. planted and natural forests), affect forest recovery [16, 17]. Many researchers have reported that forests with high stock volume densities are more sensitive to changes in water availability and more vulnerable to drought due to their greater height, larger diameter, or older age [27–31]. Other studies found that natural forests are more sensitive and vulnerable to drought than planted forests due to various human management activities and the tree age [16, 30, 32, 33]. Given the variation across forests in stock volume densities [17] and that the coverage of planted forests is increasing [34], exploring the influences of stock volume and forest type on drought legacy effects is important to effectively manage forests and accurately evaluate drought risk.

In forest ecosystems, drought legacy effects have been widely detected using field experiments (e.g. tree-ring data [20], carbon flux data [35]) and remote sensing data [23]. Nevertheless, the scarcity and relatively short duration of field experiments make it difficult to obtain a full picture of how forests respond to drought. A time series of remote sensing observations used to generate a vegetation index (VI) can provide continuous information on forest dynamics, both temporally and spatially [24, 36]. A VI is mainly driven by changes in canopy vigor, tree cover and photosynthesis rate, and thus it always serves as a proxy for gross primary production [26, 37]. Well-known vegetation indices include the enhanced vegetation index (EVI) and the normalized difference vegetation index (NDVI). Currently, the NDVI is more widely used than the EVI in research on drought legacy effects [12, 23].

Commonly used indicators for drought monitoring and assessment include the Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) [38–40]. SPEI combines the sensitivity of PDSI to changes in evaporative demand and the multiple timescales of SPI [40–42]. In detail, like PDSI, SPEI includes the influence of temperature on drought severity by means of its influence on the atmospheric evaporative demand, which represents an improvement in performance compared to SPI, which was based on precipitation data alone, when determining the impacts of drought on different ecological systems [40, 43]. Moreover, SPEI is very similar to SPI in that it considers accumulated precipitation during a period of n months and it can be compared objectively across locations with different climatologies and highly irregular precipitation distributions [39, 44]. At the same time, SPEI is based on the accumulated difference between precipitation (P) and potential evapotranspiration (PET) [40]. Thus, SPEI is widely used in research to identify and characterize dry/wet conditions by its negative/positive value [24, 45], respectively.

In this study, we focused on the forests of China and combined a remote sensing vegetation index (NDVI), forest inventory maps and a drought index (SPEI) to address the following questions: (a) Does drought have a legacy effect on forest vigor in China? (b) If so, do the forest’s properties influence its recovery path (i.e. magnitude and duration), and how? Addressing these questions will help improve the current understanding of forest recovery after drought and may help contribute to reliable evaluations and predictions of the effects of future drought events on forests.

2. Data and methods

2.1. Research area

We chose China as our study region for two reasons. First, forests are widely distributed in China and more forests have been planted there than in many other countries [46], which can be attributed to various afforestation programs [34]. Secondly, drought is one of the most damaging and disastrous hazards in China, and was found to have a significant impact on forest ecosystems [16, 47, 48].

According to the seasonal changes in the proportion of the area where the temperature (T) is less than 0 °C, we found that occurrences of T ≥ 0 °C are concentrated during June–September (figure 1(a)). Thus, to eliminate the interference of temperature variation on the response of forest vigor to drought, we focused on the warm season (June–September), because the variation in temperature in this warm
season is minimal, and the heat is not usually a restricting factor. In the forested regions of China, forest growth is highest in June–September, when it is warm (i.e. \( T \geq 0 \, ^\circ C \)) and wet (58.22% of the average annual precipitation falls in this period) (figure 1).

2.2. Data

2.2.1. Inventory maps of forest properties
Inventory maps obtained by remote sensing and large-scale field surveys [16, 17] provide data on stock volume densities, planted and natural forests, and non-forests. In detail, the map of stock volume densities was obtained from the Seventh National Forest Resources Inventory (2004–2008) based on the provincial administration and provided by each province. A total of 0.415 million permanent sample plots were chosen to acquire 0.16 billion groups of inventory data, where the data form the basis of the map [49]. The map of forest types was derived from the Eighth National Forest Resources Inventory (2009–2013), where nearly 20,000 technicians worked on the projects for 5 years (2009–2013) [50]. The forests in China were divided into five groups based on stock volume densities as follows: <30 m\(^3\) ha\(^{-1}\), 30–60 m\(^3\) ha\(^{-1}\), 60–90 m\(^3\) ha\(^{-1}\), 90–120 m\(^3\) ha\(^{-1}\), and \( \geq 120 \, m^3\, ha^{-1} \) (figure 2(a)). The maps of ‘forest type (planted and natural forests)’ include four types: planted coniferous (PC), planted mixed (PM), natural coniferous (NC), and natural mixed (figure 2(b)). Specifically, ‘natural forests’ was defined as the forests are developed naturally, or human promote their natural regeneration or initiation; ‘planted forests’ was defined as the forests that grow under artificial measures (the State Forestry and Grassland Administration of China: [www.forestry.gov.cn/gjslzyqc.html](http://www.forestry.gov.cn/gjslzyqc.html), accessed on 9 December 2021).

To acquire the digital maps of forest properties and to match up with the 1 km resolution NDVI data, first, we downloaded the maps of forest type (i.e. planted and natural forests) from their official website [50], and scanned the map of stock volume densities from their official book [49]. Next, all maps were geo-referenced based on the widely used method of ArcGIS (version 10.4) through the longitude and latitude of typical features. Then, the forest information was extracted using the classification of supervised method (ENVI, version 5.2). Finally, the maps were converted into a raster file at a resolution of 1 km through resampling using ArcGIS (version 10.4) (i.e. ‘Resample’ method), respectively. Given that the area of planted and natural forests may have changed due to multiple afforestation programs [34], only the planted and natural forest grids that were forest in the earlier period (i.e. 2004–2008 years) were selected prior to further analyses.

2.2.2. Remote sensing vegetation index
The NDVI derived from the moderate resolution imaging spectroradiometer of Terra was used to monitor forest vigor in our research. Specifically, the MOD13A3 (Version 6) dataset is a global monthly composite product available for the years 2001–2015 at 1 km resolution ([https://search.earthdata.nasa.gov/](https://search.earthdata.nasa.gov/)). As our research concentrated on the warm season (June–September), the average NDVI during June–September (\( \text{NDVI}_{ws} \)) for 2001–2015 was calculated. The low NDVI values indicated that there was no vegetation cover (the ground cover was desert, bare earth, water body, ice, glacier, etc), and considering that the average growing season \( \text{NDVI}_s = 0.1 \) was always used as the threshold value in related research [22, 23], regions with minimum \( \text{NDVI}_{ws} \) values below 0.1 during 2001–2015 were discarded from the final analysis [23, 51]. Given that the value of NDVI varies with the different forest properties, for example, NDVI increases in a nonlinear manner with the increase in stock volume/forest biomass/age/height [52–54], the original value of NDVI will interfere with our research that explores the potential impacts of forest properties on forest recovery paths. Thus, to reflect the relative changes in forest vigor and facilitate
Comparisons among forests, $\text{dNDVI}_{ws}$, was first converted to a standardized index based on the maximum value of $\text{NDVI}_{ws}$ ($\text{NDVI}_{ws,max}$) over the entire study period (i.e. 2001–2015), which was named the $\text{NDVI}_{ws}$ deficit ($\text{dNDVI}_{ws}$) (equation (1)):

$$\text{dNDVI}_{ws} [%] = \frac{(\text{NDVI}_{ws} - \text{NDVI}_{ws,max})}{\text{NDVI}_{ws,max}} \times 100.$$ 

(1)

### 2.2.3. Meteorological drought index

The widely used SPEI dataset (Version 2.5) of the Climatic Research Unit (CRU, University of East Anglia, UK) that spans 2001–2015 (http://digital.csic.es/handle/10261/153475) was selected as an indicator of drought and non-drought events in our research. The SPEI expresses the deviations of the current climatic balance (i.e. $P$ (precipitation) minus $PET$ (potential evapotranspiration)) with respect to the long-term balance, which is a standardized variate (i.e. $z$-values: mean zero and unit variance) and can be created in R software using the ‘SPEI’ package (https://cran.r-project.org/web/packages/SPEI/). The CRU SPEI data were calculated using global monthly observed meteorological datasets of $P$ and $PET$ from CRU TS3.24.01, which were interpolated to 0.5°× 0.5°. Additionally, $PET$ was estimated using the well-known formula of the FAO-56 Penman–Monteith method based on gridded mean temperature, maximum and minimum temperatures, vapor pressure and cloud cover data [55]. The SPEI timescale was chosen to be March–September ($\text{SPEI}_{Sep,7}$) because the NDVI during the growing season in this region is most closely related to SPEI over those 7 months [56]. To match the other data used (the NDVI and forest maps), $\text{SPEI}_{Sep,7}$ data were resampled to a spatial resolution of 1 km using the nearest neighbor method in ArcGIS version 10.4.

### 2.3. Methods

#### 2.3.1. Acquiring the correlations of forest vigor with water availability

The relationship between forest vigor ($\text{dNDVI}_{ws}$) and water availability ($\text{SPEI}_{Sep,7}$) was characterized by Pearson’s correlation coefficients ($r$) [22]. Then, forest pixels with significant positive $r$ values were used to explore drought legacy effects, because those forests may have been directly impacted by drought [57]. As the $r$ was calculated using values of $\text{dNDVI}_{ws}$ and $\text{SPEI}_{Sep,7}$ from 2001 to 2015 for 15 years (i.e. $N = 15$), and we selected the value of 0.1 as the significance level of the correlation coefficient, corresponding to the threshold of 0.441, the value of $|r| > 0.441$ (i.e., critical value) means significant at a 0.1 level [58]. In order to compare with other related research that includes the forest regions that exhibited non-significant positive correlations [20, 22], our research includes both significant and non-significant results.

#### 2.3.2. Defining drought legacy effects and forest recovery

Similar to previous research, we defined legacy effects in forest vigor as a departure (unitless) of the observed vigor from the predicted vigor in a period ranging from 1 to 3 years after a drought event ($\text{SPEI}_{Sep,7} < -1$) [20, 23, 59]. We take 1–3 years to study the drought legacy effect, because previous studies in China have shown that the drought legacy effects of forests last for 1–3 years [23], and most of the trees exhibited growth reductions in the last 2–3 years [60]. Here, the observed vigor was determined by the deficit of the average NDVI from June to September ($\text{dNDVI}_{ws}$). The predicted vigor was derived using the linear regression model between $\text{dNDVI}_{ws}$ and $\text{SPEI}_{Sep,7}$. The drought legacy effect at each pixel was determined by averaging the departure values between the
observed and predicted $d\text{NDVI}_{ws}$ after all drought events.

To verify the legacy effects that were characterized by the departure of the observed from the predicted vigor, we used partial autocorrelation function coefficients (PACF) to identify the extent of the lag in a time series [61]. In detail, for each pixel, the PACF was calculated based on the $d\text{NDVI}_{ws}$ data from 2001 to 2015 in R software (version 3.6.1) using the ‘tseries’ package (i.e. ‘pacf’ function) [62]. Then, the mean PACF of the forest pixels that exhibited positive and significant positive correlations between $d\text{NDVI}_{ws}$ and SPEI$_{Sep,7}$ was calculated.

According to previous studies [25, 45, 59] and the SPEI hierarchy principle [63], we recorded a drought event when SPEI$_{Sep,7}$ was less than $-1$, and the pre-drought or post-drought (non-drought) periods were when SPEI$_{Sep,7}$ was greater than or equal to 0. To avoid the inclusion of forests where drought events occurred in consecutive years and disturbed forest recovery, only single drought events (i.e. SPEI$_{Sep,7} < -1$) lasting no more than one year were considered; that is, for inclusion the forest had to have experienced non-drought conditions for 3 years before and after a single drought event (total window of 7 years). The drought scenarios are listed in table 1.

To quantify the magnitude and duration of forest recovery after a drought, we added a non-drought scenario as a reference group for the drought scenario. That is, all the water conditions were non-drought (i.e. SPEI$_{sp,7} \geq 0$) in the window of 7 years (table 1). A bootstrapped sampling method with 5000 replications was applied to estimate the confidence intervals around the average legacy effects from 1 to 3 years after drought and non-drought events. The difference in average legacy effects of drought and non-drought scenarios was used as an indicator of growth recovery. Only forest pixels that experienced two water scenarios (i.e. drought and non-drought) during 2001–2015 were considered in the analyses.

To determine whether the definition of drought and non-drought scenarios influences the magnitude and duration of forest recovery, we changed the thresholds of SPEI$_{sp,7}$ (i.e. SPEI$_{sp,7} \leq -1.5, -1.5 \leq \text{SPEI}_{sp,7} < -1, \text{SPEI}_{sp,7} < -1$), and then judged whether the results of legacy effects change. In addition, to ensure that the magnitude and duration of forest recovery after a drought were not driven by the significance level, we performed some sensitivity analyses to compare the response differences related to the values of significance levels (i.e. 0.1, 0.05 and 0.01).

### 2.3.3. Exploring the influence of forest properties on vigor recovery

We assessed the influence of forest properties on vigor recovery using separate groupings designed to characterize the properties of forests. Specifically, the stock volume density of forests that experienced drought and non-drought scenarios during 2001–2015 included three groups: $<30$, $30–60$, and $60–90$ m$^3$ ha$^{-1}$. Among those forests, only the planted and NC forest pixels with densities of $<30$ and $30–60$ m$^3$ ha$^{-1}$ were used for further analysis, because those pixels appeared simultaneously in the seventh and eighth forest inventory maps (see section 2.2.1). For each group of stock volume densities and forest type, the average legacy effects of the drought and non-drought scenarios and the difference between them (i.e. recovery) 1–3 years after were calculated. Additionally, the difference in recovery magnitude and duration for various forest properties was quantified by an independent-samples t-test (a bootstrapped sampling method with 5000 replications) and the mean PACF, respectively. To eliminate the interference of stock volume density in this assessment, the difference in vigor recovery between planted and natural forests was compared using forests with the same stock volume densities.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Previous 3 years</th>
<th>Previous 2 years</th>
<th>Previous 1 year</th>
<th>Drought/non-drought year</th>
<th>Post 1 year</th>
<th>Post 2 year</th>
<th>Post 3 year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought</td>
<td>SPEI $\geq 0$</td>
<td>SPEI $\geq 0$</td>
<td>SPEI $\geq 0$</td>
<td>SPEI $&lt; -1$</td>
<td>SPEI $\geq 0$</td>
<td>SPEI $\geq 0$</td>
<td>SPEI $\geq 0$</td>
</tr>
<tr>
<td>Non-drought</td>
<td>SPEI $\geq 0$</td>
<td>SPEI $\geq 0$</td>
<td>SPEI $\geq 0$</td>
<td>SPEI $\geq 0$</td>
<td>SPEI $\geq 0$</td>
<td>SPEI $\geq 0$</td>
<td>SPEI $\geq 0$</td>
</tr>
</tbody>
</table>

Note: SPEI represents the SPEI of September over a timescale of seven months, i.e. SPEI$_{Sep,7}$.
Figure 3. Spatial pattern of (a) all Pearson's correlation coefficients and (b) significant Pearson's correlation coefficients between forest vigor and water availability in China. Values of $|r| > 0.441$ (i.e. critical value) are significant at the 0.1 level [58]. White areas indicate non-forest areas and/or areas with minimum average NDVI during June–September lower than 0.1 over the entire study period (2001–2015).

Figure 4. Legacy effects 1–3 years after a drought or non-drought (control) event in forest regions where forest vigor exhibited (a) positive and (b) significant positive correlations with water availability, respectively. The green line represents the difference in legacy effects between drought (i.e. $\text{LE}_d$) and non-drought (i.e. $\text{LE}_n$) scenarios (i.e. recovery). The inset shows the drought legacy effect on forest vigor based on the $\text{PACF}$. Error bars represent the 95% confidence intervals around the mean from bootstrapping ($n = 5000$). $N$ represents the number of samples.

3.2. Drought legacy effects and forest vigor recovery

We found a negative legacy effect of drought on forest vigor in China, which lasted from 1 to 3 years despite drought conditions being alleviated (figure 4). Specifically, drought showed negative legacy effects on forest vigor in the first and second years post-drought. In the third year, the impact of droughts disappeared (figure 4, black bar). By contrast, the non-drought scenario showed a positive legacy effect on forest vigor that barely changed for 3 years (figure 4, white bar). The difference between the drought and non-drought scenarios highlighted the typical negative legacy effects of drought on forest vigor.

Moreover, based on the forest vigor recovery in figure 4, we found that the difference in legacy effects between the drought and non-drought scenario reduces over time and almost disappears in the third year post-drought; this was found in all regions where forest vigor exhibited positive and significant positive correlations with water availability (figures 4(a) and (b)). This finding suggests that drought causes a lagged recovery in forests, with almost full recovery only occurring in the third year following drought. These results are consistent with the results observed from $\text{PACF}$, which also revealed that drought legacies can be observed for up to 3 years post-drought (inset of figures 4(a) and (b)).

Based on the sensitivity analysis of vigor recovery to various drought definitions, shown in figure 5, we found that the forest recovery after different droughts (i.e. $\text{SPEI}_{\text{Sep},7} \leq -1.5$, $-1.5 \leq \text{SPEI}_{\text{Sep},7} < -1$, $\text{SPEI}_{\text{Sep},7} < -1$) exhibited similar qualitative patterns (figure 5). Furthermore, a one-way ANOVA test also
Figure 5. Sensitivity analysis of vigor recovery for various drought definitions. The recovery is equal to the difference in legacy effects between drought (i.e. \( \text{LE}_{\text{d}} \)) and non-drought (i.e. \( \text{LE}_{\text{n}} \)) scenarios. Drought events were characterized by \( \text{SPEI}_{\text{Sep,7}} < -1.5 \), \(-1.5 \leq \text{SPEI}_{\text{Sep,7}} < -1 \), \( \text{SPEI}_{\text{Sep,7}} < -1 \), respectively. Non-drought events were characterized by \( \text{SPEI}_{\text{Sep,7}} > 0 \). ‘Positive’ and ‘significant positive’ represent the forest regions where forest vigor exhibited positive correlations and significant (\( p < 0.1 \)) positive correlations with water availability, respectively; the error bars represent the 95% confidence intervals around the mean from bootstrapping (\( n = 5000 \)); and \( N \) represents the number of samples.

Figure 6. Sensitivity analysis of vigor recovery at various significance levels. The recovery is equal to the difference in legacy effects between drought (i.e. \( \text{LE}_{\text{d}} \)) and non-drought (i.e. \( \text{LE}_{\text{n}} \)) scenarios. Drought and non-drought events were characterized by \( \text{SPEI}_{\text{Sep,7}} < -1 \) and \( \text{SPEI}_{\text{Sep,7}} \geq 0 \), respectively. Note: ‘All positive’, ‘Positive & sig 0.1’, ‘Positive & sig 0.05’ and ‘Positive & sig 0.01’ represent the forest regions where forest vigor exhibited positive correlations, and significant positive correlations with water availability at 0.1, 0.05 and 0.01 significance levels, respectively; the error bars represent the 95% confidence intervals around the mean from bootstrapping (\( n = 5000 \)); and \( N \) represents the number of samples.

indicated that their differences in vigor recovery were not significant at the 0.1 level (\( p = 0.996 \)). In addition, compared with the response difference related to the values of significance levels (i.e. 0.1, 0.05 and 0.01), we found that the forest recovery path showed a high consistency between different significance levels (figure 6), and the one-way ANOVA test also indicated that their differences in vigor recovery were not significant at the 0.1 level (\( p = 0.998 \)). As a result, we confirm that forest recovery are not influenced by the definitions of drought and non-drought scenarios, and the significance level.

### 3.3. Forest properties impacting the recovery of forest vigor from drought

#### 3.3.1. Stock volume dependency

Similar to the results in section 3.2, all groups of forests with different stock volume densities showed negative legacy effects of drought on vigor (figure 7), but the recovery path of forest vigor differed across the various stock volume densities (figures 7(a)–(d)) in regions where forest vigor exhibited positive or significant positive correlations with water availability.

Specifically, the recovery magnitude and duration for forests with <30 \( \text{m}^3 \ \text{ha}^{-1} \) stock volume density
Figure 7. The legacy effects of drought and non-drought conditions on forests with stock volume densities of (a) <30 m$^3$ ha$^{-1}$, (b) 30–60 m$^3$ ha$^{-1}$, and (c) 60–90 m$^3$ ha$^{-1}$. (d) The difference in legacy effects between drought (i.e. LE$^d$) and non-drought (i.e. LE$^n$) scenarios (i.e. recovery). (e) Legacy effects detected by PACF. (a)–(c) and insets of (a)–(c) show the legacy effects 1–3 years after a drought or non-drought event in forest regions where forest vigor exhibited positive and significant positive correlations with water availability, respectively. Inset of (d) shows the difference in vigor recovery between forests with stock volume density <60 m$^3$ ha$^{-1}$ (including the <30 and 30–60 m$^3$ ha$^{-1}$ groups) and ≥60 m$^3$ ha$^{-1}$ (i.e. 60–90 m$^3$ ha$^{-1}$). Note: 'Positive' and 'Significant positive' represent forest regions where forest vigor exhibited positive and significant positive correlations with water availability, respectively; LE$^d$ and LE$^n$ represent the legacy effects of drought and non-drought scenarios, respectively; the error bars represent the 95% confidence intervals around the mean from bootstrapping ($n = 5000$); and $N$ represents the number of samples.

were very similar to those of forests with a stock volume density of 30–60 m$^3$ ha$^{-1}$ (figure 7(d)), so we combined the <30 and 30–60 m$^3$ ha$^{-1}$ groups into a single group of <60 m$^3$ ha$^{-1}$ (figure 7(d), red line) to compare with the forests with a stock volume density of 60–90 m$^3$ ha$^{-1}$ (i.e. ≥60 m$^3$ ha$^{-1}$; figure 7(d), blue line). We found that the recovery magnitude of forests with a stock volume density <60 m$^3$ ha$^{-1}$ was greater than that if forests with a stock volume density ≥60 m$^3$ ha$^{-1}$ in the second year post-drought ($p < 0.001$), and was still slightly greater in the third year ($p < 0.001$), but they showed no statistical difference in the first year post-drought ($p > 0.1$; figure 7(d) and table 2). This result indicates
Table 2. The difference in vigor recovery between forest stock densities <60 and ≥60 m$^3$ ha$^{-1}$ was quantified by an independent-samples t-test (a bootstrapped sampling method with 5000 replications).

<table>
<thead>
<tr>
<th>p-value</th>
<th>Post 1 year</th>
<th>Post 2 year</th>
<th>Post 3 year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>0.2442</td>
<td>0.0002</td>
<td>0.0018</td>
</tr>
<tr>
<td>Significant positive</td>
<td>0.8870</td>
<td>0.0002</td>
<td>0.0084</td>
</tr>
</tbody>
</table>

Note: 'Positive' and 'Significant positive' represent forest regions where forest vigor exhibited a positive and a significant positive correlation with water availability, respectively.

Figure 8. The legacy effects of drought and non-drought scenarios on (a) PC and (b) NC forests with stock volume density <60 m$^3$ ha$^{-1}$; (c) the difference in legacy effects between drought (i.e. LE$_d$) and non-drought (i.e. LE$_n$) scenarios (i.e. recovery); and (d) legacy effects detected by the PACF. (a), (b) and inset of (a), (b) show the legacy effects 1–3 years after a drought or non-drought event in forest regions where forest vigor exhibited positive and significant positive correlations with water availability, respectively. Note: 'Positive' and 'Significant positive' represent forest regions where forest growth exhibited positive and significant positive correlations with water availability, respectively; LE$_d$ and LE$_n$ represent the legacy effects of drought and non-drought scenarios, respectively. Error bars represent the 95% confidence intervals around the mean from bootstrapping ($n$ = 5000); and $N$ represents the number of samples.

that the magnitude of growth recovery and the recovery path are dependent on the stock volume density. The recovery magnitude of forests with low stock volume densities was mostly stronger than that of forests with high stock volume densities by the second year.

In the third year, the difference in legacy effects between drought and non-drought scenarios was close to 0 for forests with stock volume densities of <60 m$^3$ ha$^{-1}$ and ≥60 m$^3$ ha$^{-1}$ (figure 7(d)). This suggests that all forests are almost fully recovered with a three-year lag, which is consistent with the legacy effects observed in PACF (figure 7(e)).

3.3.2. Comparison between planted and natural forest

Both planted coniferous forests (PC) and natural coniferous forests (NC) showed negative legacy effects of drought on their vigor (figures 8(a) and (b)). Compared to the PC forests, the magnitude and duration of recovery of natural forests were smaller and longer (figures 8(c) and (d)). This finding was similar for all forest regions where forest vigor exhibited positive and significant positive correlations with water availability.

Given that forests with a stock volume density <30 m$^3$ ha$^{-1}$ showed a similar magnitude and duration of recovery to the forests with 30–60 m$^3$ ha$^{-1}$
stock volume density (figure 7(d)), we compared the difference in vigor recovery between planted and NC forests directly based on the <60 m² ha⁻¹ stock volume density. We found that the magnitude of recovery of NC forests was always smaller than that of PC forests 1–3 years after a drought ($p < 0.001$) (figure 8(c), table 3).

Moreover, we found that NC forests took longer to recover than PC forests, although they had a broadly similar recovery rate (figure 8(c)). As illustrated by the recovery line in figure 8, the recovery duration of NC forests was 3 years, because the difference in legacy effects between the drought and non-drought scenario was close to 0 by the third year post-drought (figure 8(c)). For PC forests, the difference in legacy effects between the drought and non-drought scenarios was greater than 0 in the third year post-drought (figure 8(c)), which indicates that PC forests returned to normal before the third year post-drought and that their vigor was better than that of natural forests. Compared with the $PACF$ of NC forests, the drought legacy effect on PC forests in the third year can be ignored because its corresponding $PACF$ is close to 0 (figure 8(d)), so the results of $PACF$ support the difference in recovery time between planted and NC forests.

4. Discussion

4.1. The mechanisms underlying forest properties’ influence on forest vigor recovery

Unlike previous studies, we used a non-drought scenario as a reference for the drought scenario, and their difference in legacy effects (i.e. the departure of observed vigor from expected vigor). This enabled us to more accurately quantify the recovery of forest vigor after drought and facilitated comparisons of different forest properties in terms of their influence on vigor recovery. Based on this method, we found pervasive and substantial legacy effects of incomplete recovery for 1–3 years after drought in forest regions of China, which is consistent with previous studies in China [23]. Moreover, our research revealed that the magnitude and/or duration of vigor recovery are dependent on the stock volume density and forest type (i.e. planted or natural forests). NC forests with high stock volume densities were more severely impacted by drought legacy effects; this was not found, or was poorly understood in previous research [15, 20, 21, 59].

Understanding the physiological and ecological mechanisms underpinning drought legacy effects is the basis to understanding vigor recovery. Drought leads to crown defoliation [64], decreases in tree height and radial growth [65], and a decline in root biomass and carbon uptake [66]. It also causes water table depletion [15, 25] resulting in the cavitation and loss of hydraulic conductivity and impaired water transport [67]. In addition, it alters carbon allocation among leaf, root and wood growth, affecting carbohydrate storage and fruiting [65]. Thus, even when water conditions return to normal, the vigor of surviving trees does not rapidly recover, probably due to delayed water table replenishment [15, 25], lower water transport capacity [20, 21], and increased carbon allocation to root non-structural carbohydrates [66].

Forest vigor recovery varies depending on different forest properties, and these differences are probably induced by site-specific characteristics (e.g. climatic conditions), the capacity for water uptake and transport, etc. To further understand the drivers of recovery differences, we explored the differences in climatic conditions between various forest properties (i.e. stock volume and forest type). The climatic conditions included the mean annual temperature, the mean annual photosynthetic active radiation, the mean annual precipitation and the mean annual soil moisture level. Finally, we found that the climatic conditions of different forest properties exhibited similar qualitative patterns (figure 9), which indicated that the recovery differences between the various forest properties are not controlled by climatic conditions, but by other factors such as the tree height and age, etc [27]. Specifically, as forests with high stock volume are typically taller, have larger diameter trees, or trees that are older [27], the increased height, size and age of trees could augment maintenance respiration costs and soil water demand, reducing the efficiency of the hydraulic pathway, increasing the hydraulic constraints and xylem cavitation risks under drought conditions [28–31], which results in the poor recovery of forests with high stock volume. Additionally, NC forests may recover slower and less effectively than PC forests because planted forests receive more human management, such as human selection (e.g. site), plowing and irrigation [33, 68]. Furthermore, the lower resistance of natural forests compared with planted forests may be because natural forests are older [30, 32].

In addition, our research also carried out a sensitivity analysis of vigor recovery for various drought definitions and significance levels (figures 5 and 6). Based on this analysis, we found that they did not significantly influence the forest recovery after a drought. Thus, we think that the forest type and stock
The climatic conditions of various forest properties: (a)–(d) stock volume densities, (e)–(h) PC and NC forests. The forest pixels of (a)/(b)/(c)/(d) are those explored in figure 7, and the forest pixels of (e)/(f)/(g)/(h) are those explored in figure 8. All forest pixels that exhibited positive correlations between forest vigor and water availability were considered in those figures. The bars and error bars represent the mean value and standard deviation of data, respectively.

The cumulative frequency and box plots (inset) of per pixel warm season integrated NDVI in 2001–2015. The warm season represents the months of June to September. The forest pixels are those that were explored in figure 7, and all forest pixels that exhibited positive correlations between forest vigor and water availability were considered in those figures. The number of samples was 10,605 (707 × 15, <60 m$^3$ ha$^{-1}$) and 1785 (119 × 15, ≥60 m$^3$ ha$^{-1}$). The saturation point of NDVI was 0.8 [69].

volume are the main influence factors on its recovery path at regional scale in China, highlighting that understanding the influence of forest properties on vigor recovery is important when assessing drought legacy effects.

4.2. Uncertainties and prospects

We took several steps to reduce the uncertainty of our results, such as using a standardized NDVI to compare different forests, eliminating the interference of non-forests by removing pixels that did not appear in the early forest inventory maps, and removing pixels with minimum NDVI values below 0.1. In addition, we only focused on the response of forest vigor to drought during the warm season (i.e. June–September) to remove the interference of other impact factors (i.e. temperature). In addition, we explored the difference in NDVI between various stock volume densities (figure 10). We found that all stock volume densities showed a tiny percentage of NDVI saturation (i.e. NDVI > 0.8 [69]) and they exhibited similar qualitative patterns (figure 10). Thus, we think that the observed difference in recovery between various stock volume densities was
not caused by NDVI saturation (or NDVI nonlinearity with biomass). Our research focused on the forest regions that exhibited positive correlations between water availability and forest vigor, which include the forest regions that exhibited non-significant positive correlations. However, the percentage of those non-significant regions is too small (about 18%) to influence our main results. The 0.5° resolution of the CRU climatic dataset may be considered relatively coarse; thus, to determine whether the CRU dataset can characterize the actual water conditions, we calculated the SPEI_{Sep,7} based on 593 stations of observed meteorological variables in China and conducted a Pearson's correlation analysis (i.e. $r$) with those locations in the CRU dataset for 2001–2015. We found that 92.4% ($p < 0.05$) and 95.4% ($p < 0.1$) of meteorological stations showed a high consistency (i.e. significant positive $r$) between values derived from the CRU dataset and those derived from observation stations (figure 11).

However, there are still some limitations in our research. It is possible that there are some errors in the forest inventory we used and in the spatial resolution resampling process. Moreover, there were a limited number of forest pixels that experienced both drought and non-drought scenarios due to the short time series of the research data. Therefore, more matched data in time and space are needed in the future to continue to decrease these uncertainties.

5. Conclusions

The legacy effects of drought on forests have been widely discussed in the existing literature, but knowledge gaps remain regarding whether legacy effects are dependent on forest properties such as stock volume and forest type. To that end, our research addressed two related scientific questions and found that: (a) drought has a legacy effect on forest vigor in China, which is pervasive and lasts from 1 to 3 years; and (b) a forest’s properties (i.e. stock volume and forest type) influence its recovery path (i.e. magnitude and duration); we point out that NC forests with a high stock volume are more severely impacted by drought legacy effects, which may have implications for forest management with regard to reducing the risk of drought in the future in more vulnerable forests.

Data availability statement

All data generated or used during the study appear in the article.

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