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Satellite evidence of canopy-height dependence of forest drought resistance in southwestern China

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Abstract

The frequency and intensity of drought events are increasing with warming climate, which has resulted in worldwide forest mortality. Previous studies have reached a general consensus on the size-dependency of forest resistance to drought, but further understanding at a local scale remains ambiguous with conflicting evidence. In this study, we assessed the impact of canopy height on forest drought resistance in the broadleaf deciduous forest of southwestern China for the 2010 extreme drought event using linear regression and a random forest (RF) model. Drought condition was quantified with standardized precipitation evapotranspiration index (SPEI) and drought resistance was measured with the ratio of normalized difference vegetation index during (i.e. 2010) and before (i.e. 2009) the drought. At the regional scale we found that (a) drought resistance of taller canopies (30 m and up) declined drastically more than that of canopies with lower height under extreme drought (SPEI < -2); (b) RF model showed that the importance of canopy height increased from 17.08% to 20.05% with the increase of drought intensities from no drought to extreme drought. Our results suggest that canopy structure plays a significant role in forest resistance to extreme drought, which has a broad range of implications in forest modeling and resource management.

1. Introduction

Forests are one of the most important natural resources in the world. They provide extensive ecosystem services ranging from producing food, fuel, shelter, medicine and fresh air (Hendrey *et al* 1999, Carle and Holmgren 2008) to watershed protection, erosion prevention and climate mitigation (Patric 1976, Lu *et al* 2001, Canadell and Raupach 2008). Several lines of evidence indicate that the frequency, intensity, and duration of land drought events have been increasing along with global climate warming (Yi *et al* 2014, 2015, Toby 2020), which have substantial impacts on the structure and function of forest ecosystems. Insufficient water during drought can affect the material transport in trunk conduits of trees, which may result in the damage of conductive vessels (Delzon and Loustau 2005, Niu *et al* 2014). Severe drought may cause widespread tree mortality and dieback, and even forest degradation across the region (Huang *et al* 2015, Kolb 2015). Consequently, the impact of drought can be assessed with the changes of forest structure and functions.

The impact of drought on forests essentially depends on which part of the forests are more sensitive to water deficit (Bennett *et al* 2015). Greater impacts on short and small trees may modify future forest succession whereas greater impacts on tall and large trees causes disproportionate losses of carbon reserve (Phillips *et al* 2010, Lindenmayer *et al* 2012). Previous studies have reached a general consensus on the size-dependency of forest resistance to drought (Francesco *et al* 2018, Xu *et al* 2018a, 2018b, 2018c). But further understanding at the mechanistic level remains ambiguous and controversial. It is unclear whether large (tall) or small (short) trees would suffer more under drought stress. Some studies indicated that small and short trees suffered more because of their shallow roots and less available water in the deep soil (Nakagawa *et al* 2000, Guarín and Taylor 2005, Zhang *et al* 2017, Francesco *et al* 2018, Liu *et al* 2022), while other studies indicated that drought had a greater impact on large and tall trees because they have a greater evapotranspiration rate and higher water demand (Aber *et al* 2001, Nepstad *et al* 2007, Zhang *et al* 2009, Xu *et al* 2018a, 2018b, 2018c). Both views were mainly based on the results from field measurements and control experiments at local scale or site level. These conclusions are greatly affected by site specificity and sample size, and it is challenging to extrapolate the pattern at a larger scale. Since canopy height and structure can be readily changed by human activities, a solid understanding on size-dependent forest resistance to drought at regional scale would provide valuable scientific guidance for policy and practice of forest management (Bellassen and Luyssaert 2014).

As an efficient data acquisition tool, remote sensing observation can provide high spatial-temporal resolution images for forestry related research at a large scale with continuity. Various vegetation indices are based on the contrast that green leaves strongly absorb radiation in the red wavelengths and reflect radiation in the near-infrared (Assal *et al* 2016). Previous studies showed those vegetation indices are sensitive to various biophysical parameters (such as leaf area index, crown closure and water content of leaves) that could be used to indicate vegetation growth status at a large scale (Deshayes *et al* 2006). Normalized difference vegetation index (NDVI) is one of the most widely used satellite-based algebraic indices allowing cross-site comparation, which leverages different parts of the electromagnetic spectrum for disturbance assessment (McDowell *et al* 2015), which is suitable for monitoring vegetation growth change from mesoscale to large scale (McManus *et al* 2012, Vicente-Serrano *et al* 2013). When vegetation declines as a result of climate stress (such as drought and high temperature), NDVI will decrease. On the contrary, when the environmental condition is favorable for vegetation growth, NDVI will increase. Therefore, NDVI is suitable for quantifying the impact of climate change on vegetation growth (McManus *et al* 2012, Vicente-Serrano *et al* 2013, Huang *et al* 2015). Remote sensing-based VI allows rapid assessment of forest dynamic changes in response to climate stress such as drought at a regional scale, but often overlooks the role of stand structure in forest response to drought (Assal *et al* 2016).

In this study, we attempted to assess the forest resistance to drought in southwest China. The objective of this study was to quantify the role of canopy height and its relative importance in forest resistance to drought.

2. Materials and methods

2.1. Study region

The study area was located in southwestern China, including the Yunnan, Guizhou, Guangxi and Sichuan provinces and Chongqing municipality (figure 1), which historically had ample precipitation and water resources. Periodically, heavy rains brought by EL NIÑO events such as in 1997/1998 and 2015/2016 also impact the region (Fan *et al* 2017). However, regional droughts have appeared more and more frequently since 1950 due to a combination of climate change, deforestation, land use change and degradation of hydrological facilities (Qiu 2010, Zhang *et al* 2013, Zhang and Zhou 2015). Southwestern China experienced a severe drought event in 2010, which had a substantial impact on the local forest ecosystems with widespread mortality and dieback. Since the 'Grain for Green' program (GGP, an ambitious conservation program initiated in 1999 that involved 25 provinces in China to restore cultivated land into forest and pasture) was implemented in this area (Xiao 2014), many new trees were planted which complicated the structure of forest canopy. Therefore, with existing high plant biodiversity in this region, southwestern China was an interesting region in which to study the effects of canopy height on forest drought resistance (Xu *et al* 2018a, 2018b, 2018c).

The forest distribution map (figure 1) was based on the MODIS land cover product (MCD12Q1, Version 6) global land cover types at yearly intervals derived from six different classification schemes (https://modis.gsfc.nasa.gov/). Land cover data derived from IGBP (International Geosphere-Biosphere Programme) classification schemes was used in this study, with a spatial resolution of 500 m in 2010. The main forest types in southwestern China included mixed forest, broadleaf deciduous forest (BDF), broadleaf evergreen forest and needleleaf deciduous forest (table 1). Combined with standardized precipitation evapotranspiration index (SPEI) data, we found that 17.04% of the forest suffered

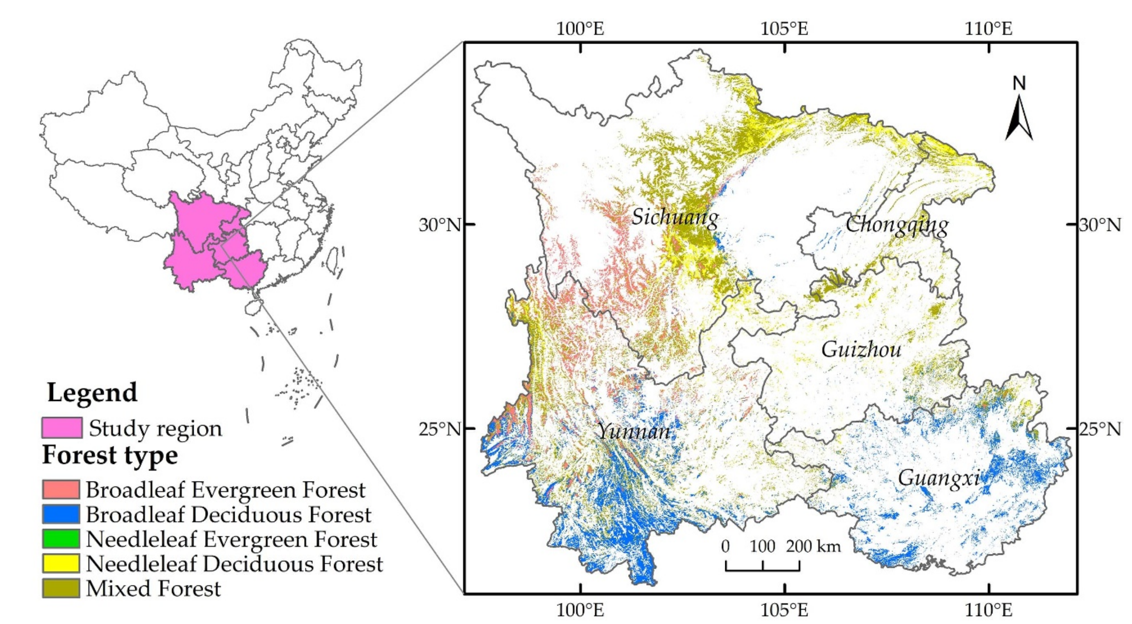

Figure 1. The study region and its forest distribution at a resolution of 500 m based on the MODIS land cover product (MCD12Q1, Version 6) derived from IGBP classification schemes.

Table 1. Composition of forest types and proportion of the forest affected by 2010 drought in southwestern China.

Forest types	Proportion	Suffering from drought
Broadleaf evergreen forest	16.6%	2.4%
Broadleaf deciduous forest	28.5%	7%
Needleleaf evergreen forest	0	0
Needleleaf deciduous forest	11.1%	0.77%
Mixed forest	43.9%	6.87%
Total	100%	17.04%

from severe drought in 2010. BDF was the type of forest that was affected most by the 2010 drought in the area, which was chosen as the subject of this study.

2.2. Climate data

The SPEI was used to indicate drought intensity and quantify surface water deficit and surplus in this study (Vicente-Serrano *et al* 2010a, 2010b, 2013). SPEI data (figure 2) were obtained from the global SPEI data set, which was based on monthly precipitation and potential evapotranspiration from the Climatic Research Unit of the University of East Anglia (http://sac.csic.es/spei/database.html). This data provided SPEI timescales between 1 and 48 months, with a half degree spatial resolution and a monthly temporal resolution. To correspond to the time scale used for the NDVI data (see section 2.3), SPEI of July 2009 and 2010 with 12 month period was chosen for the analysis (Vicente-Serrano *et al* 2010b). Based on its SPEI value, drought intensity of a year could be classified into one of the seven categories: extreme drought (SPEI < -2), severe drought ($-2 <$ SPEI $\leqslant -1.5$), moderate drought ($-1.5 <$ SPEI $\leqslant -1$), near normal ($-1 <$ SPEI $\leqslant 1$), moderate wet ($1 <$ SPEI $\leqslant 1.5$), severe wet ($1.5 <$ SPEI $\leqslant 2$), extreme wet (SPEI > 2) (McKee *et al* 1993, Dorman *et al* 2013). Previous studies have shown that previous year's moisture condition may have a legacy effect on the vegetation growth of current year (Gao *et al* 2018, 2020). In order to control the confounding effect of previous year's condition, we only included pixels whose SPEI for the previous year (i.e. 2009) was near normal ($-1 <$ SPEI $\leqslant 1$) in our analysis, which accounted for 89.8% area of BDF in the study area.

2.3. Satellite data

2.3.1. NDVI data

MODIS-NDVI product (MOD13A3, Version 6) from 2009 to 2010 was used in this study. Vegetation indices data were provided monthly at 1 kilometer (km) spatial resolution in MOD13A3 product (https://modis.gsfc.nasa.gov/). The NDVI average from July to August of the year was calculated to represent forest growth for that growing season (Xu *et al* 2018b, 2018c).

2.3.2. Canopy height map

The forest canopy height map at the resolution of 1 km (figure 3) was produced by airborne LiDAR canopy height models using the Geoscience Laser Altimeter System aboard ICESat (Ice, Cloud, and land Elevation Satellite) and global ancillary variables (https://landscape.jpl.nasa.gov) (Simard *et al* 2011). Zhang *et al* (2014a) verified the accuracy of the canopy height dataset in southwestern China using field survey data. The determination coefficients of the regression of LiDAR-based canopy height over observed tree height from field measurements was $R^2 = 0.6263$ ($n = 202$, RMSE $= 4.18$ m) (Zhang *et al* 2014a).

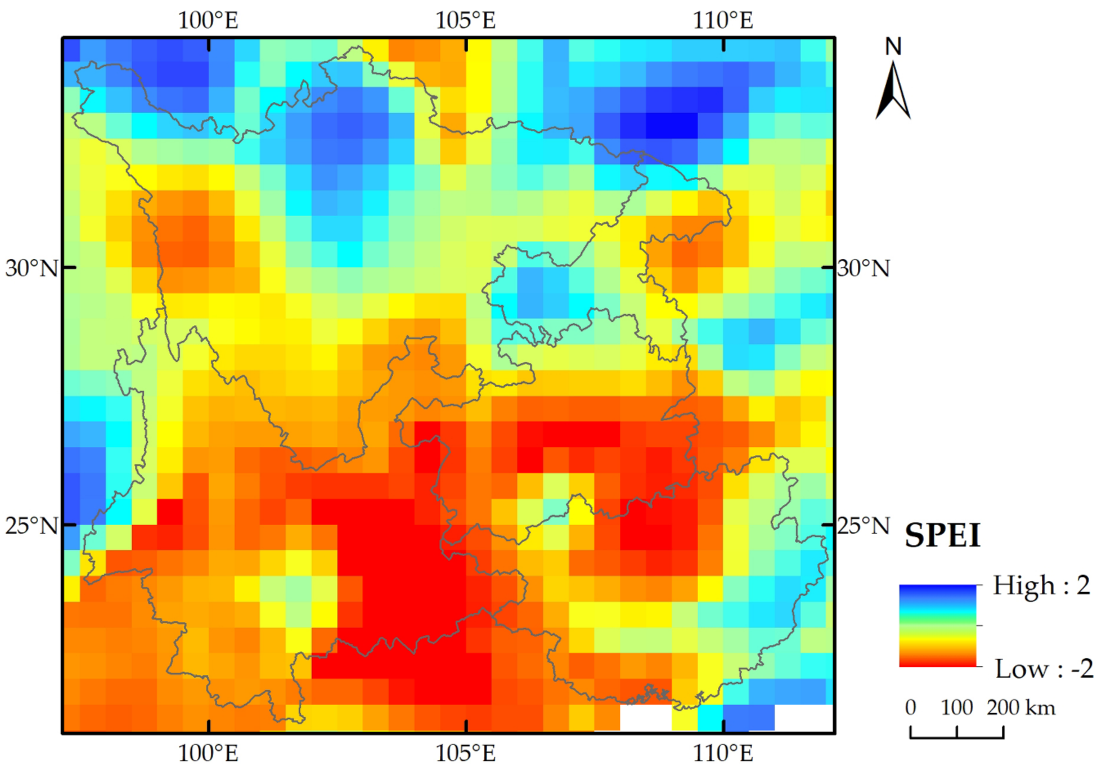

Figure 2. Standardized precipitation evapotranspiration index (SPEI) of July 2010 with 12 month time scale in the study region at a resolution of half degree.

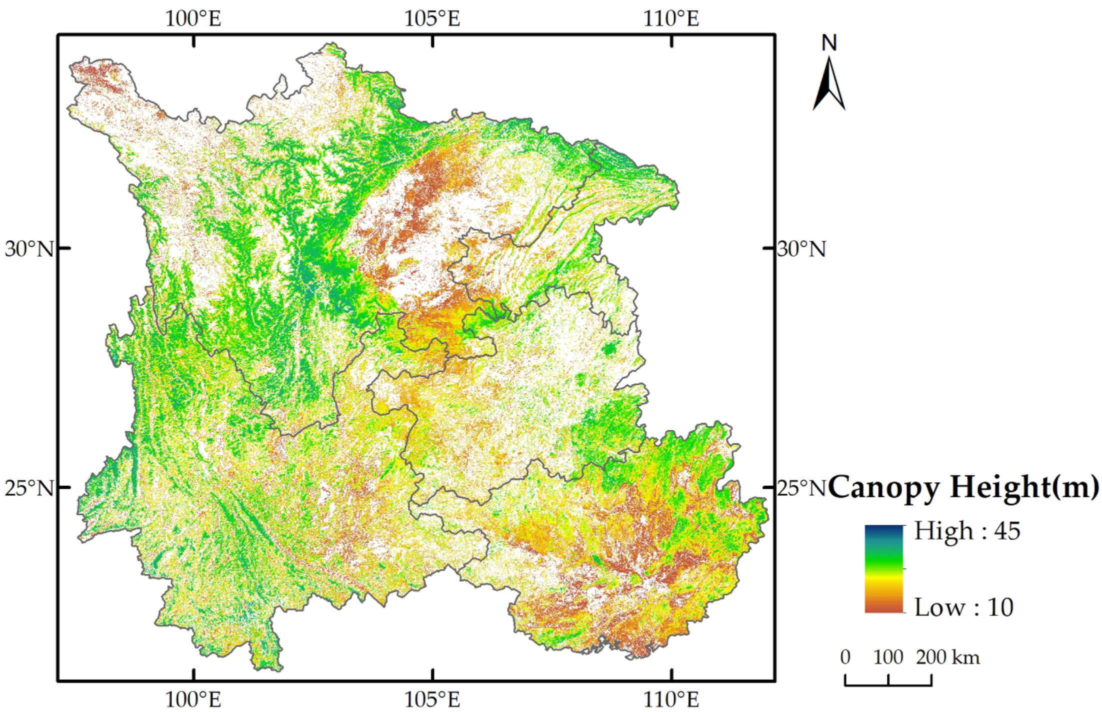

Figure 3. The distribution of forest canopy height in the study region at a resolution of 1 km.

2.4. Auxiliary data

The digital elevation model (DEM) data was derived from the Shuttle Radar Topography Mission (SRTM) data of the U.S. Space Shuttle Endeavour (Jarvis *et al* 2008). The data set was resampled based on the latest SRTM V4.1 data, with a spatial resolution of 1 km. The soil texture data was from Shangguan *et al* (2013), with a spatial resolution of 1 km. This data describes the composition ratio of clay, sand and silt soil. The vertical profile of soil property was captured in eight layers to the depth of 2.3 m (i.e. 0–0.045 m, 0.045–0.091 m, 0.091–0.166 m, 0.166–0.289 m, 0.289–0.493 m, 0.493–0.829 m, 0.829–1.383 m and 1.383–2.296 m). We used the averages of top four layers (up to 0.289 m deep) for our analysis. Based on correlation analysis (table S2 available online at stacks.iop.org/ERL/17/025005/mmedia), we chose the least correlated pair (clay and silt, $r = -0.039$) among three soil texture variables as input variables for random forest (RF) models.

All the spatial data projections were converted to WGS84 coordinate system, and resampled to 1 km resolution based on canopy height data by the nearest neighbor algorithm. All regression analyses were conducted in EXCEL (Microsoft Office 2016), and graphs were made in IDL8.5 and Arcgis10.0.

2.5. Forest drought resistance

Resistance is considered as reversal of the reduction in ecological performance during disturbance, and it is estimated as the ratio between the performance during and before the disturbance (Kaufman 1982, Lloret *et al* 2011, Zhang *et al* 2014b). In this study, forest drought resistance (Rt) corresponds to the ratio between growth rates during the drought and immediately before the drought (Zhang *et al* 2014b, Yi and Jackson 2021). It was calculated as the ratio between NDVI in 2010 and 2009 pixel by pixel by:

$$\text{Resistance}\,(Rt) = \frac{\overline{\text{NDVI}_{\text{Dr}}}}{\overline{\text{NDVI}_{\text{PreDr}}}}$$

where $\overline{\text{NDVI}_{\text{Dr}}}$ represents the growth during the 2010 growing season (July and August) in drought and $\overline{\text{NDVI}_{\text{PreDr}}}$ represents the growth during the 2009 predrought growing season. Based on the 2010 Atlas of Natural Disaster in China (Chinese National Database of Natural Resources and GIS 2010), the most dominant natural disaster was drought, second by patchy surface fires in confined areas partially exacerbated by drought. Forest clearcut was minimal in this region, due to the Grain to Green project initiated in 2000. Therefore, Forest drought was the single most dominant driver of NDVI change from 2009 to 2010.

2.6. Statistical analysis

Forest resistance to drought is affected by both external water conditions and internal attributes such as canopy structure. In order to assess forest growth response to drought stress under different canopy heights, statistical analyses were conducted in two-ways as follows:

(a) We lined up all the pixels with their canopy heights, SPEI and Rt values. All the BDF pixels in southwestern China were divided into three categories based on canopy height: canopy height $\leqslant$20 m, 20 m < canopy height $\leqslant$30 m, and canopy height >30 m. Each category was then further divided into four groups based on SPEI in 2010: extreme drought (SPEI < -2), severe drought ($-2 <$ SPEI $\leqslant -1.5$), moderate drought ($-1.5 <$ SPEI $\leqslant -1$), and no drought ($-1 <$ SPEI $\leqslant 1$). Mean and standard deviation of drought resistance were calculated for each SPEI-canopy height combo category. Forest resistance to drought were compared among different drought conditions (SPEI), and the impact of canopy structures on forest resistance were compared among three canopy height groups.

(b) We grouped all the pixels with SPEI in 2009 within $(-1, 1]$ into four groups based on SPEI in 2010 (SPEI < -2, $-2 <$ SPEI $\leqslant -1.5$, $-1.5 <$ SPEI $\leqslant -1$, and $-1 <$ SPEI $\leqslant 1$), which were referred to as under extreme drought, severe drought, moderate drought, and no drought. Under each drought condition, average and standard error of resistance with identical canopy heights were calculated. To avoid outliers tipping off the regression lines, canopy height categories with less than 1% of the total forest pixel numbers were omitted from the final analysis. Regression models of Rt average over canopy height were established under similar drought conditions.

2.7. RF model

To quantitatively assess forest size-dependent resistance to drought, we used RF algorithm to analyze the contribution of canopy structure (canopy height), water condition (SPEI), elevation (DEM), soil texture (clay and silt) to forest drought resistance. The RF was an effective algorithm for optimizing learning accuracy without obviously complicating the calculation, and it has been widely used in geography and ecology research (Cutler *et al* 2007, Schwalm *et al* 2017, Wei *et al* 2017, Du *et al* 2019). We used the RF internal variable importance measures to assess the impact of canopy height on forest drought resistance by using all the pixels. The importance indicator %IncMSE measured the increase of the mean square error (MSE) as a result of the tested variable being permuted (values randomly shuffled) (Du *et al* 2019, Ye *et al* 2019). The higher the value of %IncMSE, the more important the variable in the out-of-bag cross-validation process in explaining forest drought resistance (Breiman 2001, Du *et al* 2019). We also used RF model to assess the importance of canopy height under extreme drought (SPEI < -2), severe drought ($-2 <$ SPEI $\leqslant -1.5$), moderate drought ($-1.5 <$ SPEI $\leqslant -1$) and no drought ($-1 <$ SPEI $\leqslant 1$) for comparison. The RF algorithm was implemented using the RF package available in the Python environment (Du *et al* 2019, Wang *et al* 2019).

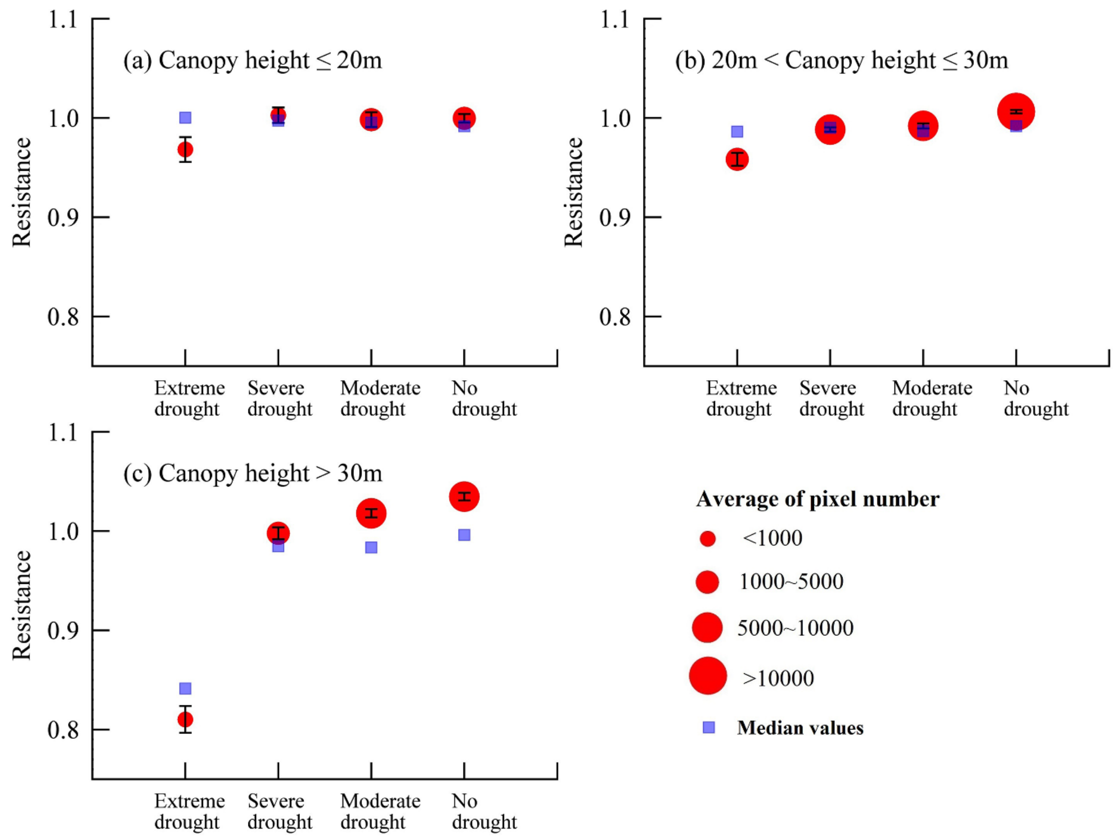

Figure 4. Forest resistance to drought with different intensities among canopy height categories. The red circle represents the mean, the size of the circle represents the number of pixels, and the blue square represents the median values. Error bars are means ± 1 standard error.

3. Results

3.1. Impact of drought severity on forest resistance

The mean resistance (±1 standard error) of a BDF with a short canopy (<20 m) was 0.968 ± 0.012 under extreme drought (SPEI < −2.0), 1.002 ± 0.008 under severe drought (−2.0 < SPEI ⩽ −1.5), 0.998 ± 0.007 under moderate drought (−1.5 < SPEI ⩽ −1.0) and 1.000 ± 0.004 with no drought (−1.0 < SPEI ⩽ 1.0) (figure 4(a)). The BDF mean resistance with an intermediate canopy (20 m < height ⩽ 30 m) was 0.958 ± 0.006 under extreme drought, 0.988 ± 0.002 under severe drought, 0.992 ± 0.003 under moderate drought, and 1.006 ± 0.002 with no drought (figure 4(b)). The BDF mean resistance with a tall canopy (>30 m) was 0.81 ± 0.013 under extreme drought, 0.998 ± 0.006 under severe drought, 1.018 ± 0.004 under moderate drought, and 1.035 ± 0.004 with no drought (figure 4(c)). These results suggested that forest resistance to drought declined as drought severity increased, with the least resistance being under the extreme drought condition. Such decline of forest resistance is also canopy size dependent. When canopy height was over 30 m, resistance dropped drastically (as low as 80%). These results indicated that BDF might have size-dependent resistance to drought and the resistance of taller forests was more sensitive to water condition than shorter forests.

3.2. Relationship between forest drought resistance and canopy height

Linear regression models were established between forest resistance and canopy height under extreme drought, severe drought, moderate drought, no drought (figure 5, tables S3–S6). Resistance of forests with various canopy heights was less than 1 which indicated that forest growth declined. There was a significant negative correlation between forest drought resistance and canopy height, and forest drought resistance declined significantly with the increase of canopy height under extreme drought condition ($p < 0.001$, figure 5(a)). When canopy heights were over than 30 m, the resistance decreased dramatically with canopy heights (green line in figure 5(a)). When the canopy height was over 30 meters, forest drought resistance decreases by 0.041 for every meter increase in canopy height, while forest drought resistance only decreased by 0.0037 for every meter increase in canopy height as canopy height less than 30 meters (figure 5(a)). In contrast, regressions of DBF resistance to drought under less than extreme drought, regardless of canopy heights, were around 1 which indicated that forest growth was not affected. There

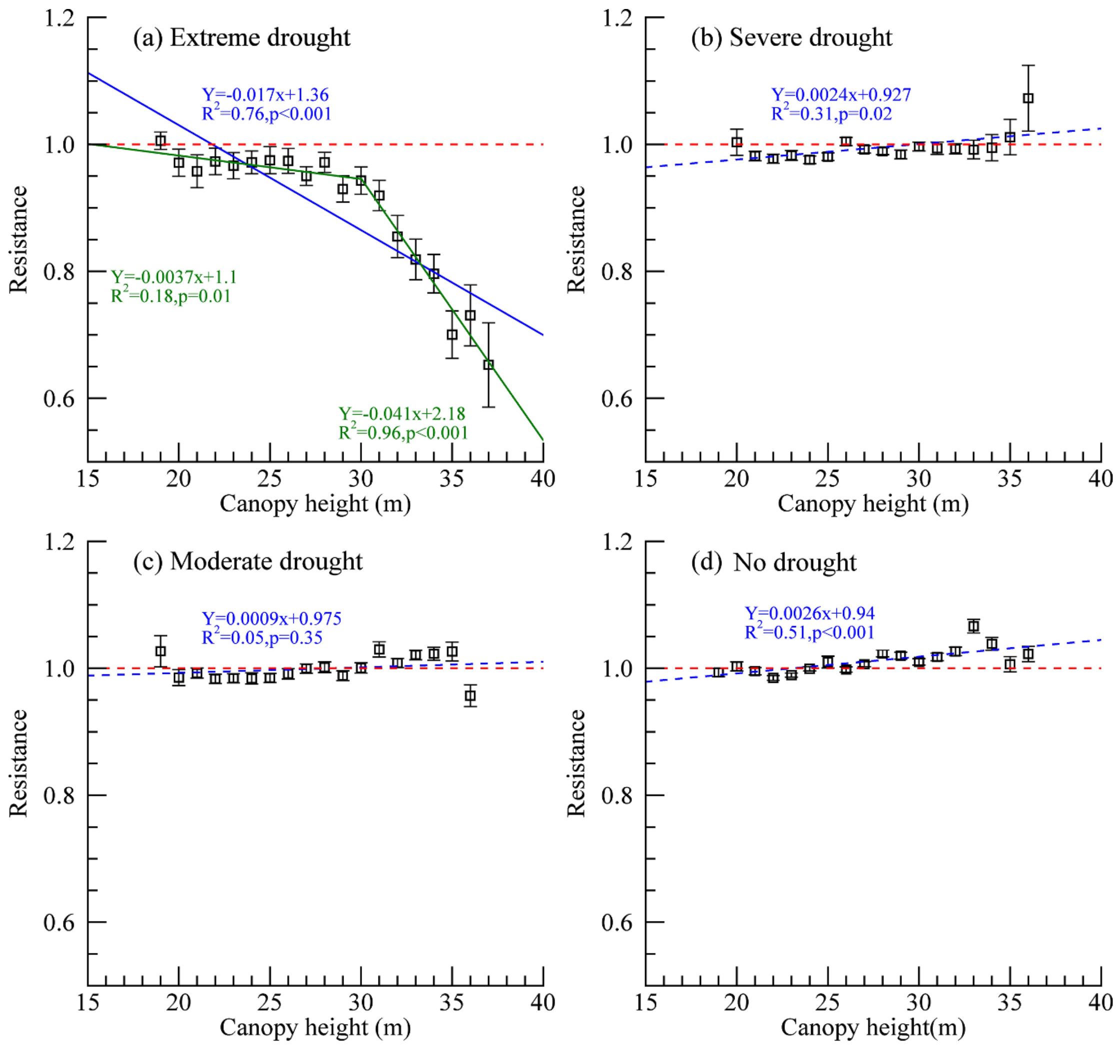

Figure 5. The relationships between canopy height and forest resistance under extreme drought ((a), SPEI < -2), severe drought ((b), $-2 <$ SPEI $\leqslant -1.5$), moderate drought ((c), $-1.5 <$ SPEI $\leqslant -1$), no drought ((d), $-1 <$ SPEI $\leqslant 1$). Error bars are means $\pm$ 1 standard error, and the red dashed line indicates a resistance value of 1, i.e. no change in NDVI values.

was a weak linear correlation between forest drought resistance and canopy height, and forest drought resistance increased slightly with the increase of canopy height under less than extreme drought conditions (figures 5(b)–(d)). Those results suggested that forest resistance to extreme drought was size-dependent and taller forests had a weaker resistance to drought than shorter forests. But the relationship between canopy height and forest drought resistance changed with the change of water conditions. In other words, forest drought resistance is only size dependent under extreme drought, the improvement of water conditions could change this dependence.

3.3. Relative importance of canopy height to forest drought resistance

RF model for drought resistance in BDFs in southwestern China showed that the importance of elevation was 51.27%–55.76%, and that of soil texture were 16.82%–20.99% for all four drought conditions with no consistent patterns (table S1). However, the importance of canopy height increased steadily from 17.08% to 20.05% with the increase of drought intensities (from no drought to extreme drought condition, with decreasing SPEI) (figure 6). Although the influence of environment variables was dominant, the influence of canopy heights over forest resistance to drought increased with drier conditions.

4. Discussion

4.1. Forest drought resistance distinguished by canopy height

Our analyses on satellite data have shown forest drought resistance is not only affected by water condition but also depends on canopy structure at the regional scale in southwestern China (figures 4 and 5). In the past decades, some of the results showed that small trees are more vulnerable, while some suggested that drought have a greater impact on large trees (Nakagawa *et al* 2000, Guarín and Taylor 2005, Zhang *et al* 2017, Francesco *et al* 2018). Compared with previous studies, this study addressed the two opposite findings at a much larger scale which is

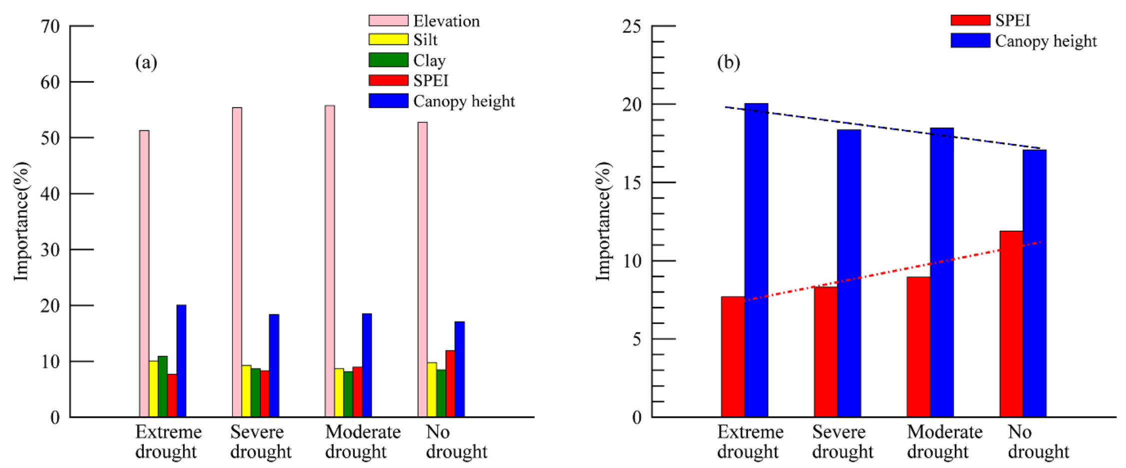

Figure 6. The importance (%) of elevation, soil texture, standardized precipitation evapotranspiration index (SPEI) and canopy height to forest drought resistance under different drought conditions (a). Panel (b) the dashed lines indicate that the importance values of canopy height (blue) decreased and SPEI (red) increased with decreasing drought intensity.

a very important variable for forest ecology and management, and the result might substantially improve the prediction of future tree growth and mortality in southwestern China (Stovall *et al* 2019).

Generally, our results support the hypotheses that at local scale and site level, larger and taller forest would suffer more from growth reduction during drought regardless of the spatial scale employed (Zhang *et al* 2009, Xu *et al* 2018c). Recent studies have also shown that compared with variables such as saturated vapor pressure difference, maximum temperature, precipitation, effective water storage, vegetation coverage and slope, tree height is the most powerful variable for predicting tree mortality (Stovall *et al* 2019). There are three mechanisms potentially contributing to the canopy-height-dependent responses: physiology and metabolism requirement of individuals with different height (Eamus *et al* 2013, Sevanto *et al* 2014), competitive or nursing interaction with neighboring trees (Mueller *et al* 2005, Andivia *et al* 2018), and accumulative effects and legacy effects of various dimensions of the drought regime (Gao *et al* 2018, 2020).

Firstly, large and tall trees have a greater evapotranspiration rate and higher water demand than small and short trees, a big disadvantage to drought resistance (Zhang *et al* 2009). For taller trees, they have a longer vertical water conducting passage from root to canopy, requiring a greater pulling force against gravity generated by transpiration. As water deficit decreases the transpiration rate, the pulling force would be insufficient to transport water to the canopy through xylem, leaving taller trees more vulnerable to embolism and desiccation with a lower drought resistance (Cochard *et al* 2021). Under drought conditions, extensive root systems also grant larger trees a higher likelihood of absorbing water with air. The air would form bubbles in the xylem to block the conduits and affect the material transport, which may result in tree mortality or growth decline. In addition, carbon sequestration and storage increase with age, peak around 22 years then decline (Zhou *et al* 2015). Net primary production increases with stand age before stabilizing while the metabolism of large trees consumes more dry matter, which collectively increases the risk of mortality in large trees (Waggoner and Turner 1971).

Secondly, individuals with different statures may experience different interactions with neighboring trees, ranging from fierce resource competition at the canopy height to being sheltered from heat and drought at the sub-canopy level (Mueller *et al* 2005, Andivia *et al* 2018). Competition as large trees are much stronger than small ones due to their higher demand in radiation, water and nutrients.

Thirdly, there are different facets and dimensions of drought regime that may trigger differential responses to trees with different sizes and ages. Drought frequency (number of dry months) and duration (maximum number of consecutive dry months) resulted in 'cumulative effects' which amplified the impacts of drought on trees and reduced the drought resistance of trees. Onset timing and severity of drought increased legacy effects on tree stem radial growth, which reduced the drought resilience of trees (Gao *et al* 2018). Although taller trees may have a more extensive root system for absorbing soil water, the intensity of extreme drought was high enough to deplete soil moisture at a deeper level like in the case of 2010 drought in southwestern China, greater damage would happen to taller trees (Xiao 2014, Xu *et al* 2018c).

4.2. Implication of canopy height-dependent forest drought resistance

With global warming, the frequency and duration of drought would increase worldwide in the near future reported by IPCC5 (Stocker 2014). Human activities (e.g. deforestation and afforestation) have drastically altered the structure and functions of forests (Xiao 2014). Recent satellite data (2000–2017) reveal a greening pattern that is strikingly prominent in China and India. China alone accounts for 25% of the global net increase in leaf area with only 6.6% of global vegetated area, and 42% of the greening in China is from afforestation (Chen *et al* 2019). Such human activities have profoundly impacted forest distribution and structures, including age structure and canopy structure. Forest canopy-height-dependent resistance to drought provides a new perspective and evidence on managing forest in the context of climate change. Humans might reduce forest drought-related mortality or dieback by manipulating the forest structure, specifically by removing tall trees and filling the gaps with transplanting or natural regeneration.

Although the economic value and ecosystem functions of forests increase with age and size over time (Blanco 2012), their vulnerability to drought stress also increase with age and size based on this study. Although taller trees may have a disproportionally higher growth rate, it could be due to their greater light exposure (Araujo *et al* 2020). Based on the results of this study, proper management of forest canopy structure (i.e. removing aging tall trees that higher vulnerability to drought) would expose subcanopy trees to more light and boost their productivity, and also manage the risk of dieback during extreme drought events.

Our results will also shed new light on optimization of process-based ecological modeling. Many computer simulations models of forest, such as Forest Vegetation Simulator (Crookston and Dixon 2005), Bio-Geochemical Cycle model used by the USDA (United States Department of Agriculture), are based on the assumption of equilibrium (Running and Gower 1991, Zhou *et al* 2015). The input and output of energy and nutrients in a system in equilibrium are in dynamic balance with no net gain or loss over time. This does not hold true for most systems except the climax communities. If we consider the stage structure of the community and factor in its spatial heterogeneity and uncertainty when modeling a forest community, the model would be more realistic and provide more accurate predictions.

4.3. Uncertainty

The data used in this study include MODIS products, LiDAR inversion data and gridded climate data. The spatial resolution of those data is not exactly the same, so the deviation of data matching is unavoidable. Although NDVI is sensitive to spectral change caused by disturbance for a wide range of canopy coverage, it could get saturated at very high vegetation coverage and lead to bias (Xu *et al* 2019). When canopy defoliation takes place during a drought, the NDVI could pick up spectral reflections from the understory which may lead to an underestimate of NDVI change. NDVI could also be biased by pixels covered by cloud. We used MODIS-NDVI product from July and August of 2009 and 2010. As for the reliability of MODIS NDVI data, pixels evaluated as good (class 0) and marginal (class 1) provided reliable data, while data in pixels covered with snow/ice (class 2) or cloudy (class 3) were not reliable. The percentage of pixels with reliability class 0 or 1 was 75.45% and 89.89% for 2009, 70.57% and 88.60% for 2010, respectively, with an average of 81.13%. Only 18.87% pixels were cloudy, which was much lower than the long-term average of over 50% (2001–2014) (Xu *et al* 2018c). Canopy height is the key data in this research; other spatial data were resampled to match the canopy height data. The canopy height data used here were derived from the LiDAR rather than from the field observations, which was one of the best approaches currently available describing forest vertical structure at regional scales (Simard *et al* 2011). From known validation at the regional scale, this canopy height data has a good correlation with the field observation tree height in southwestern China reported by Zhang *et al* (2014a). It is undeniable that this canopy height data also has its own variance and uncertainty, but the canopy heights in our study area (ranged from 15 m to 35 m) were much larger than the regional errors (RMSE = 4.18 m, $R^2 = 0.6263$). The correlation coefficient (r) between canopy height and elevation is weak ($r = 0.349$) which modest enough to be both included in the RF model, but it might affect the value of the importance. Gazol *et al* (2018) suggested that evergreen gymnosperms and deciduous angiosperms have different adaptations and physiological mechanisms to cope with drought, with the former displaying a lower resistance but faster recovery based on tree ring data (TRWi). Although TRWi data were generally more sensitive than NDVI data in terms of accessing resilience to drought (Gazol *et al* 2018), TRWi data from deciduous broadleaf forest in southwest China is rare and patchy.

5. Conclusions

In this study, we revealed the characteristics of forest canopy heights related drought resistance based on satellite data and reprocessed climate data. Our results demonstrated that forest resistance to extreme drought depended on canopy height in southwestern China. Taller forests were more vulnerable and susceptible to growth reduction during severe drought than shorter ones. The shorter forests had a greater drought resistance. The frequency and duration of severe drought have been predicted to increase in the near future, more attention should be given to canopy structure for forest management and climate related risk assessments.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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