**Title:** Warmer spring temperatures in temperate deciduous forests advance the timing of tree growth but have little effect on annual woody productivity

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**As the climate changes, warmer spring temperatures are causing earlier leaf-out1–4,5 and commencement of net carbon dioxide (CO2) sequestration2,4 in temperate deciduous forests, resulting in a tendency towards increased growing season length1,4,5 and annual CO2 uptake2,4,6–10.** **However, less is known about how spring temperatures affect tree stem growth11,12, which sequesters carbon (C) in wood that has a long residence time in the ecosystem13,14.** **Using dendrometer band measurements from 440 trees across two forests, we show that warmer spring temperatures shifted stem growth of deciduous trees earlier but had no consistent effect on peak growing season length, maximum growth rates, or annual growth.** **The latter finding was confirmed on the centennial scale by 207 tree-ring chronologies from 108 forests across eastern North America, where annual growth was far more sensitive to temperatures during the peak growing season than in the spring.** **These findings imply that any extra CO2 uptake in years with warmer springs6–8 does not significantly contribute to increased sequestration in long-lived woody stem biomass.** **Rather, contradicting current projections from global C cycle models2,3,15,16, our empirical results imply that warming spring temperatures are unlikely to increase woody productivity enough to strengthen the long-term CO2 sink of temperate deciduous forests.**

In recent decades, tree growth in Earth’s forests has more than offset losses from deforestation and other disturbances, such that a net forest CO2 sink of ~1.6 Gt C yr-1 offsets ~20% of anthropogenic emissions17, dramatically slowing the pace of atmospheric CO2 accumulation and climate change. Of this important C sink, ~ 47% occurs in temperate forests17, with temperate deciduous forests sequestering >0.3 Gt C yr-1.18 The future behavior of this C sink will play an important yet uncertain role in influencing atmospheric CO2 and climate change19–21.

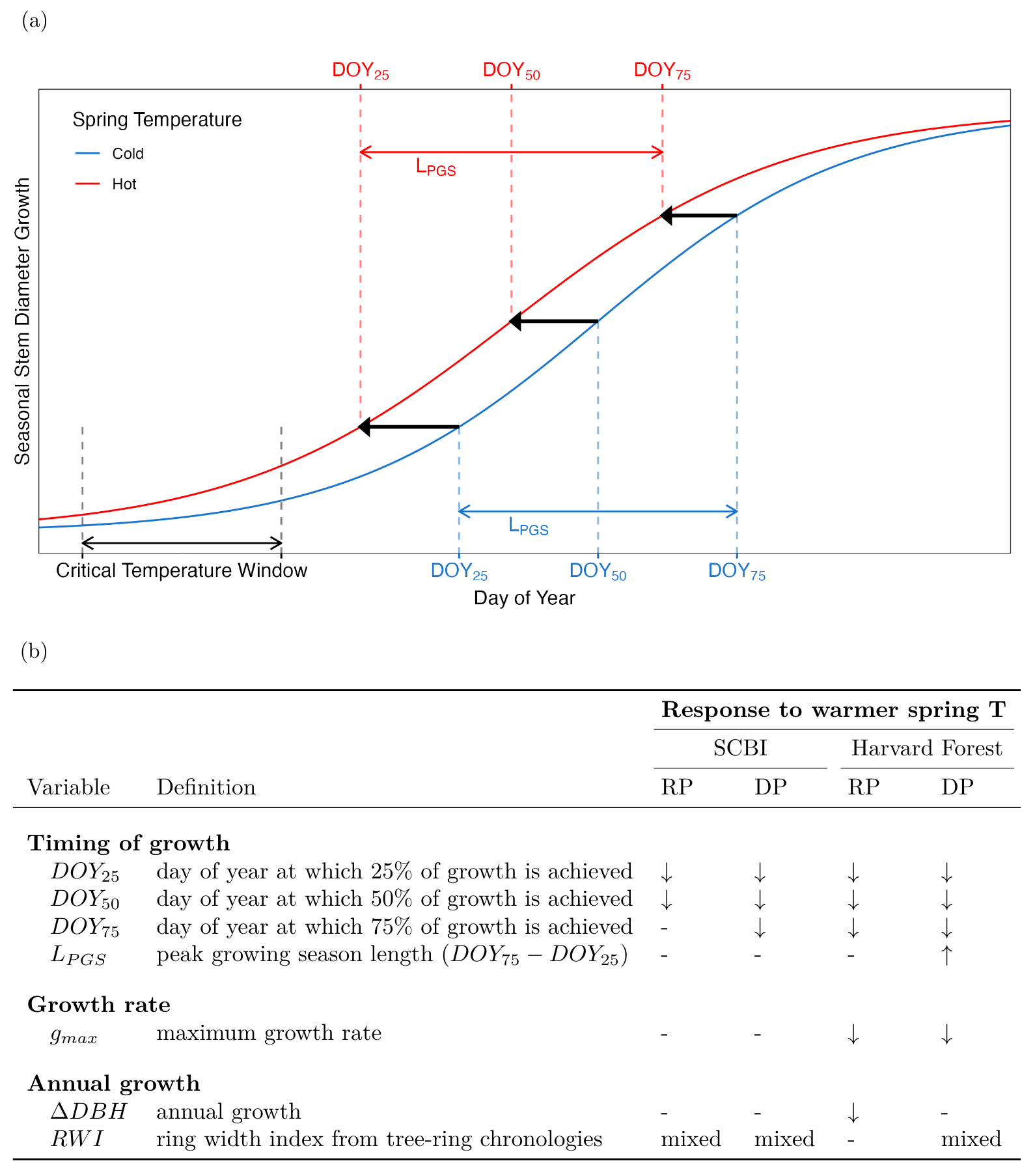
In temperate deciduous forests, spring warming generally lengthens the period over which trees have photosynthetically active leaves1, 22 and that over which the ecosystem is a net CO2 sink2,22. Based on these observations, current terrestrial ecosystem models effectively assume that longer growing seasons lead to sustained increases in annual net CO2 uptake (i.e., net ecosystem exchange, NEE)2,3,15,16, as occurs when additional C is allocated to woody growth and therefore resides in the ecosystem for decades to centuries13,14. However, model representation of C allocation to stem growth is overly simplistic and does not capture known decoupling of stem growth from photosynthate production12,21,23. As a result, the consequences of rising spring temperatures on stem growth – or woody aboveground net primary productivity (ANPPwoody) on the ecosystem level – may not be accurately represented in models12,21. Understanding the sensitivity of ANPPwoody to spring temperatures is central to predicting the future of the temperate deciduous forest C sink.

Most studies on tree growth responses to warmer spring temperatures have focused on boreal or temperate conifers, which tend to respond to warmer spring temperatures with an earlier start to growth24, 25 and increased annual growth in mesic climates26, 27. In contrast, we have little evidence as to how stem growth and ANPPwoody respond to warmer spring temperatures in deciduous forests11,12. Close coordination of budburst and initiation of xylogenesis12 suggests that warm springs should shift the onset of growth earlier alongside observed advances in leaf phenology1–4,5. However, earlier initiation of growth would not necessarily translate to earlier, faster, or greater stem growth; rather, stem growth is dependent upon environmental conditions on hourly to daily time scales28,29, and annual growth is more closely linked to conditions within the growing season than to growing season length30, gross primary productivity (GPP)23, or NEE23. Furthermore, growth of broadleaf deciduous trees may be sink-saturated21, such that longer growing seasons with more C fixation do not necessarily augment growth15,23,31. Tree-ring records, which can be used to examine relationships of annual growth to temperature but not to understand growth seasonality, reveal that growth of temperate deciduous trees tends to be most sensitive to temperature or potential evapotranspiration between late spring and early summer32,33, with some evidence that warmer springs may have a modest, but usually insignificant, positive effect on growth27,33. These observations do not necessarily align with the finding that warming spring temperatures increase annual forest CO2 uptake in temperate deciduous forests2,22. Characterizing responses of stem growth to warming spring temperatures is critical to bridging this conceptual disconnect and understanding how forest biomass growth is likely to change as the climate warms.

Here, we evaluate how spring temperatures affect stem growth timing, growth rates, and annual growth of temperate deciduous trees across eastern North America. To test whether warmer springs advance the timing and extend the duration of stem growth, we used dendrometer band measurements on 440 trees across two mid-latitude forests. To test whether spring temperatures consistently increased annual growth, we analyzed 207 tree-ring chronologies from 108 forests.

## Dendrometer band analysis

Using dendrometer band measurements taken throughout multiple growing seasons at the Smithsonian Conservation Biology Institute (SCBI; Virginia, USA; n = 119 trees from 2011-2020) and Harvard Forest (Massachusetts, USA; n = 321 trees from 1998-2003), we fit a logistic growth model34 to determine the days of year (DOY) when 25, 50, and 75% annual growth were achieved (*DOY25*, *DOY50*, *DOY75*), peak growing season length (*Lpgs = DOY75 - DOY25*), the maximum growth rate (*gmax*; occurs on average within 5 days of *DOY50*), and total annual increment in diameter at breast height (; Fig. 1). This analysis was performed separately for ring- and diffuse porous species (Extended Data Table 1), which differ in the seasonal timing of growth(Extended Data Table 2)29,35. These stem-growth milestones were compared to canopy foliage phenology (measured at ecosystem level via remote sensing).



**Figure 1 | Summary of temperate deciduous tree growth responses to warmer spring temperatures.** (a) Schematic illustrating parameters of interest and summarizing predominant responses of each to warmer maximum temperatures during a ‘critical temperature window’, defined as the period with the strongest control over *DOY25*; (b) Variable definitions and summary of responses to warmer spring temperatures at two temperate forests – Smithsonian Conservation Biology Institute (SCBI) and Harvard Forest – and for two groups of broadleaf deciduous species (RP=ring porous; DP=diffuse porous), where up and down arrows indicate increases and decreases that are significant both statistically (p<0.05) and biologically (effect size >3%C-1), ‘-’ indicates no significant correlation, and ‘mixed’ indicates a mix of significant and non-significant correlations, often in different directions.

Both canopy foliage phenology and the timing of stem growth shifted earlier as spring temperatures increased (Fig. 2, Extended Data Figures 4-5). We found a consistent effect of temperature (*Tmax* or *Tmin*) throughout the spring, but the strongest effects on stem growth timing were found using *Tmax* during a critical temperature window (CTW). CTW was identified by measuring the correlation between weekly *Tmax* and *DOY25* for all combinations of consecutive weeks from January 1 to mean *DOY25* for each xylem architecture-site combination (Extended Data Figure 3). The CTW was defined as the weeks for which this correlation was strongest, and mean *Tmax* during this period (CTW *Tmax*) used as our independent variable.



**Figure 2 | Responses of foliage phenology (a,b) and stem growth timing (c,d) to spring temperatures at the Smithsonian Conservation Biology Institute (a,c) and Harvard Forest (b,d).** Panels (a-b) show ecosystem-level canopy foliage phenology from 2001-2018, obtained from the MODIS Global Vegetation Phenology product (MCD12Q2.006) for a single pixel at the center of each ForestGEO plot, where G = Greenup, M=Mid-greenup, P=peak, and S=Senescence (i.e., beginning of green-down). Panels (c-d) show the dates at which stem growth milestones were achieved, on average, for sampled populations of ring porous and diffuse porous trees at SCBI (2011-2020) and Harvard Forest (1999-2003). Mean *DOY25*, *DOY50*, and *DOY75* were estimated using the Bayesian model visualized, with confidence intervals, in Extended Data Figure 4. Mean maximum temperature (*Tmax*) was calculated for each xylem architecture/site combination over the respective critical temperature window (CTW), then turned into a ratio and assigned a color on a gradient where the coldest year in the sample is blue and the warmest is red. Leaf phenology years are colored according to the CTW *Tmax* of the porosity group containing the dominant canopy species at each site (diffuse porous at SCBI, ring porous at Harvard Forest).

For ring- and diffuse- porous species at both sites, warmer CTW *Tmax* resulted in earlier achievement of seasonal milestones. Consistent with findings from previous studies, leaf phenological milestones advanced at both sites (Fig. 2a-b, Extended Data Table 2), with greenup (DOY when EVI2 first crossed 15% of the segment EVI2 amplitude) advancing 3.45 days/C at SCBI (p=0.016) and 2.4 days/ C at Harvard Forest (p=0.1). Similarly, with the exception of ring porous *DOY75* at SCBI, the stem growth milestones *DOY25*, *DOY50*, and *DOY75* decreased with CTW *Tmax* (Figs. 1, 2c-d; Extended Data Figures 4-5). Specifically, *DOY25*, *DOY50*, and *DOY75* advanced 0-1.7 days/ C for ring porous species and 2.8-2.9 days/ C for diffuse porous species at SCBI, and 10.3-12.3 days/ C for ring porous species and 0.9-4.2 days/ C for diffuse porous species at Harvard Forest (Extended Data Table 2).

Whereas the length of time between canopy greenup and senescence (*i.e.,* the day when greenness dropped below 90% of its peak) increased with the CTW *Tmax* of the porosity group containing the dominant canopy species at each site (diffuse porous at SCBI, ring porous at Harvard Forest; Fig. 2a-b), there was no consistent lengthening of *Lpgs* (Fig. 1, Extended Data Figures 4-5).

In contrast to the pronounced effects of CTW *Tmax* on the timing of growth, its effects on *gmax* and were weak and inconsistent (Fig. 1, Extended Data Figures 4-5). Specifically, *gmax*, which occurred very close to *DOY50*, displayed extremely small negative changes (Harvard Forest) or changes in opposite directions (SCBI) in relationship to CTW *Tmax* for ring- and diffuse- porous species. displayed a weak positive relationship (+0.0029-0.008 cm/ C) with CTW *Tmax* at SCBI and a weak negative relationship (-0.02-0.003 cm/ C) at Harvard Forest (Extended Data Figure 4).

## Tree-ring analysis

To understand how annual growth increments have responded to spring temperatures at the centennial scale, we analyzed tree-ring chronologies of 12 species at SCBI33 and 4 species at Harvard Forest (Extended Data Table 1), plus an additional 191 chronologies from 106 sites (Fig. 3; Extended Data Figure 1; Extended Data Table 3)32. In total, our analysis included 207 chronologies representing 24 broadleaf species at 108 sites distributed from Alabama (34.35N latitude) to Michigan (45.56N latitude) and spanning a 15 C range in April *Tmax*. Across all chronologies, the standardized ring-width index (RWI) was significantly (at p 0.05) positively correlated with April *Tmax* for only 2% of chronologies: 1 of 142 ring porous and 4 of 66 diffuse porous species-site combinations (Extended Data Table 3). There were even fewer significant positive correlations with March and May *Tmax*: 0% and 1%, respectively (Extended Data Table 3). In contrast, RWI was frequently negatively correlated with *Tmax* during peak growing season months (May-August), with significant correlations for 52% (May: 45/141, Jun: 107/141, Jul: 91/141, Aug: 53/141) and 46% (May: 10/66, Jun: 52/66, Jul: 36/66, Aug: 23/66) of species-site-month combinations for ring porous and diffuse porous species, respectively. *Tmin* generally exhibited weaker relationships to annual growth than *Tmax*, with few significant correlations between spring *Tmin* and RWI (Extended Data Figure 6).

To test whether warm springs might result in storage of non-structural carbohydrates (NSC) that would augment growth the following year36, we extended the analysis to examine correlations between RWI and *Tmax* in the previous year (Extended Data Figure 7). This revealed little effect of previous spring temperatures on annual growth, with significant positive correlations of RWI to previous March or April *Tmax* for 5/142 ring porous chronologies and to previous April or May *Tmax* for 7/66 diffuse porous chronologies.

To test whether the negative effect of summer temperatures might offset an enhancement of growth by warmer spring temperatures, we tested for the joint effects of April and June-July *Tmax* on RWI. Results were qualitatively similar to the univariate correlations (Fig. 3), with significant (at p = 0.05) positive correlations to April *Tmax* for only 4% of chronologies and significant negative correlations with June-July *Tmax* for 77% of chronologies (Extended Data Table 3).



**Figure 3 | Sensitivity of annual growth, as derived from tree-rings, to monthly mean maximum temperatures (*Tmax*), for 207 chronologies from 108 sites across eastern North America** (Extended Data Figure 1). Colors indicate the correlation between monthly *Tmax* and a dimensionless ring width index (RWI) derived from the multiple trees that form each chronology and emphasizing interannual variability associated with climate. Chronologies are grouped by xylem porosity and ordered by mean April *Tmax*. Plots are annotated to highlight records from our two focal sites, the Smithsonian Conservation Biology Institute (SCBI) and Harvard Forest (HF) (Extended Data Table 1). Species analyzed and numbers of significant correlations to *Tmax* are summarized in Extended Data Table 3, and chronology details are given in SI Table 1.

## Discussion

Together, our results demonstrate that warmer spring temperatures in the temperate deciduous forests of eastern North America advance the timing of stem growth but have little effect on total annual growth (Figs. 1-3). The observed advance in stem growth under warmer springs parallels advances observed for canopy foliage phenology (Fig. 2a-b)2,4,5 and NEE2,4. However, inconsistent with the concept that an earlier start to growth would increase ANPPwoody, we demonstrate that warmer springs either hasten the deceleration of stem expansion or otherwise fail to translate extended growing seasons into biologically significant increases in stem growth (Fig. 1), and thereby have negligible effect on total annual growth for most species and locations (Fig. 3). Our observations suggest that the deceleration of stem expansion, which occurs mid-summer near the time of peak canopy greenness (Extended Data Figure 2)4,30, is driven by cues other than photosynthate limitation, such as water stress, daylength, or sink limitation15,28,30,37,12, 23. This adds to a growing body of evidence for a sink limitation of stem growth21,23, wherein global change factors known to enhance photosynthesis, such as longer growing seasons or elevated CO2, do not cause a corresponding increase in stem growth30,38.

Combined with widespread observations that warming springs tend to lengthen the season of C sequestration4,22 and increase net C sequestration2,4,6–10, our findings imply a lengthening of the period from peak stem growth to the cessation of CO2 uptake by the ecosystem and an increase in C allocated to functions other than stem expansion in the current or following year (Extended Data Figure 7). It remains theoretically possible that warm springs could augment ANPPwoody, which, although routinely calculated based on stem growth, can be partially decoupled from it through differences in wood density or C content23. Extra C fixed in years with warm springs could potentially be allocated to formation of more C-dense wood, either through enhanced cell wall thickening (a process that lags behind stem expansion39) or to a higher ratio of high-density latewood to lower-density earlywood. However, existing evidence indicates that vessel features are most strongly controlled by summer drought stress in the previous (earlywood) or current (latewood) year, while warm springs have a neutral or negative effect on latewood width40–42. Thus, it is unlikely that warm springs have a positive effect on total C content of annual rings or ANPPwoody. The fate of any additional C fixed during years with warm springs remains unresolved, but possible destinations – including respiration, NSC storage, and production of foliage, reproductive structures, roots31, or root exudates – generally have shorter residence times than woody growth. Indeed, when GPP of a mature forest was increased through experimental CO2 enrichment, ANPPwoody remained unchanged, while additional C was released back to the atmosphere on relatively short time scales through enhanced respiration38. Consistent with this, it has been observed that C gains from an earlier spring can be offset through fall or winter respiration3,43, although even the C in shorter-lived pools would often be carried over into the following year44. Thus, observed augmentation of NEE by warm springs2,9,10 is likely to be compensated by increased respiration in subsequent years.

It is possible that as spring warming continues, forests will adjust to directional changes in growing season length with an enhancement of ANPPwoody. Across latitudinal gradients, warmer spring temperatures are associated with earlier leaf-out45 and longer growing seasons, which in turn are correlated with greater tree growth46, ANPPwoody47, and NEE48. Thus, warming spring temperatures are likely to increase the biophysical potential for annual tree growth. If extra photosynthate made available through a growing difference between GPP and ANPPwoody is allocated to functions that relieve limitations on woody growth – for example, by enhancing nutrient and water acquisition through enhanced allocation to roots31,49 – it is possible that warming spring temperatures could ultimately increase ANPPwoody through indirect mechanisms. Understanding how warming spring temperatures are influencing C allocation within ecosystems remains an important outstanding question.

Regardless of the influence of spring temperatures on C cycling within the ecosystem, our results clearly demonstrate that the dominant effects of temperature on deciduous tree growth occur not in the spring, but during the peak growing season of the current or sometimes previous year (Fig.3, Extended Data Figure 7), when increased atmospheric demand associated with high temperatures can limit both leaf-level gas exchange and stem growth23,28,30,50. Indeed, the timing of peak growth in June and July (Extended Data Table 2, Extended Data Figure 2) coincides with the timing of the greatest sensitivity of annual growth to *Tmax* (Fig. 3, Extended Data Table 3). This finding is consistent with numerous tree-ring studies demonstrating strong sensitivity of growth to drought stress or high temperatures during the peak growing season26,32,33,46. Warm springs may also amplify summer drought stress in some times and places, effectively canceling out any positive effects of an extended growing period3,51,52. While such an interaction was unlikely to have played a major role within the scope of our dendrometer band study, given relatively mesic conditions and lack of significant correlation between spring temperatures and summer drought stress (see Methods), our tree-ring analysis does reveal a higher frequency of negative than positive correlations of annual growth to spring temperatures, particularly for ring porous species in cooler climates (Fig. 3, Extended Data Table 3). Thus, warm springs can have a net negative effect on growth, particularly when water is limiting27.

As spring temperatures become increasingly warmer, growing seasons will start earlier. However, barring rapid acclimation of temperate deciduous forests to the warming conditions, advancement in the timing of stem growth (Fig. 1) is unlikely to provide the sustained increase in CO2 sequestration in woody biomass and ensuant negative climate change feedback that is anticipated in most climate forecasting models2,3,15,16. Rather, the dominant effect of rising temperatures on forest woody productivity will be a negative effect of high summer temperatures (Fig. 3), which constitutes a positive feedback to climate change.

# Methods

## Dendrometer band analysis

Dendrometer band measurements were collected at SCBI53 and Harvard Forest4,35, both part of the Forest Global Earth Observatory (ForestGEO)54,55. SCBI (38.8935° N, 78.1454° W; elevation 273–338 m.a.s.l.) is located in the Blue Ridge Mountains at the northern end of Shenandoah National Park, 5 km south of Front Royal, Virginia. The forest is secondary and mixed age, having established in the mid-19th century after conversion from agricultural fields53. Dominant canopy species within the 25.6 ha ForestGEO plot include tulip poplar (*Liriodendron tulipifera* L.), oaks (*Quercus spp.*), and hickories (*Carya spp.*)33. The climate is humid temperate, with 1950-2019 mean annual precipitation of 1018 mm and temperatures averaging 1°C in January and 24°C in July46. Within the study period for the dendrometer band analysis (2011-2019), spring temperatures (March and April *Tmax*; source: CRU v.4.0456) and summer Standardized Precipitation Evapotranspiration Index (SPEI)57 values (4-month value of August) were similar to the average climate prior to the study period (1970-2010). Specifically, average spring *Tmax* was 16.9 1.4°C (mean 1SD) prior to the study period (range: 14.1-19.9) and 17.6 1.7°C (range: 15.6-20) during the study period, while summer SPEI was -0.06 1.02 (range: -1.7-2.4) prior to the study period and 0.5 0.8 (range: -0.8-1.6) during.

Harvard Forest (42.5388° N, 72.1755° W, 340-368 m.a.s.l.) is located near the central Massachusetts town of Petersham. The forest is secondary and mixed age, having re-established around the beginning of the 20th century following agricultural use and significant hurricane damage in 1938. Dominant species within the 35 ha ForestGEO plot are hemlock (*Tsuga canadensis* (L.) Carrière), oak (*Quercus spp.*) and red maple (*Acer rubrum* L.). The climate is temperate continental, with 1950-2019 mean annual precipitation of 1104 mm and temperatures averaging -5°C in January and 22°C in July46. Within the study period for the dendrometer band analysis (1999-2003), spring temperatures (March and April *Tmax*; source: CRU v.4.0456) and summer SPEI values (4-month value of August) were similar to the average climate prior to the study period (1970-1998). Specifically, average spring *Tmax* was 10.9 1.5°C prior to the study period (range: 8.0-13.2) and 11.2 1.0°C (range: 10.1-12.2) during the study period, while summer SPEI was 0.1 0.9 (range: -1.8-1.7) prior to the study period and 0.2 0.9 (range: -1.0-1.1) during. The driest summer during the study period (1999) had the 5th lowest SPEI value (-1.0) in the period 1970-2003, with precipitation of 52 mm mo-1 in June-August compared to average monthly precipitation of 100+ mm35.

Metal dendrometer bands were installed on 941 trees within the SCBI and Harvard Forest ForestGEO plots. Bands were placed on dominant species, including two diffuse- and two ring porous species at SCBI and eight diffuse- and three ring porous species at Harvard Forest (Extended Data Table 1). While we do not estimate the ages of trees in our sample, bands at both sites were placed on individuals of differing sizes in an attempt to measure trees across a range of ages. Bands were measured with a digital caliper approximately every 1-2 weeks within the growing season from 2011-2020 at SCBI and 1998-2003 at Harvard Forest. The number of bands measured at each site fluctuated slightly as trees were added or dropped from the census (e.g., because of tree mortality). Across years, the number of bands sampled averaged 129 (range: 91-138) at SCBI and 717 (range: 700-755) at Harvard Forest. In total, our analysis included 2210 tree-years (Extended Data Table 1).

Measurements were timed to begin before the beginning of spring growth and to continue through the cessation of growth in the fall. At SCBI, the median start date was April 14, which was adjusted forward when early leaf-out of understory vegetation was observed, with the earliest start date being March 30 (in 2020). Measurements were continued through to fall leaf senescence, with the median end date being October 17 and the latest end date November 26 (2012). At Harvard Forest, all measurements from 1998 were dropped because of a late start date (May 26). Among the remaining years,the median start date was April 21 and median end date of October 27. 1999 was an anomalous year where initial measurements were taken on January 5, but not taken again until April 15. The latest end date was November 11, 2002. In our analysis, each band-year was treated independently, with no data overlap from one year to the next.

The raw dendrometer band data were screened before analysis to remove records or entire tree-years that were either unreliable or inappropriate for our analysis. First, we manually screened the data for three classes of errors. First, when a measurement was drastically different from previous and following measurements, it was assumed to be a human error and removed. Second, when measurements remained essentially unchanged for several readings, followed by a sudden jump then return to a normal growth pattern, this was assumed to be a case where the band was stuck on the tree bark and then released. In these cases, the full annual record for the tree was removed. Third, data points that deviated substantially from normal growth patterns, but for unknown causes, were removed. If a majority of the data points fell into this class within a tree-year, the entire year was removed from the analysis. We also removed tree-years with small or negligible total growth ( cm; SCBI = 26, Harvard Forest = 253), and tree-years where first intraannual measurement was later than the first spring survey (trees that were missed in the initial census; SCBI = 22, Harvard Forest = 8). These were removed because they reduce the reliability of predicted growth in the modeled curves.

We fit a five-parameter logistic growth model34 to dendrometer band data from each tree-year to define stem growth milestones and growth rates (Fig. 1). In particular, we model the observed diameter at breast height (DBH) on a given day of the year (DOY; *i.e.*, julian days) as:

Here, and are lower and upper asymptotes of the model. *DOYip* is the day of year where the inflection point in growth rate occurs, shapes the slope of the curve at the inflection point, and is a tuning parameter controlling the slope of the curve toward the upper asymptote. This allows an asymmetric fit to the data, where the onset of growth can be estimated independent of the cessation of growth. When , *gmax* occurs on *DOYip*. The model outputs two additional variables, and , which represent the beginning and end DBH in each model year. We used the first and last manual dendrometer band measurements as starting points to calculate these two variables. With this method, initial measurements too late in the growing season which miss the start of the growing season can cause incorrect estimations of and . The 1998 survey at Harvard Forest recorded first measurements on May 26, which is less than 2 weeks away from the average DOY25 at this site. This late start made the calculation of timing and total growth variables unreliable, so we removed tree years in 1998 from our analysis. The model was fit in R v4.0 using the functions developed in the *Rdendrom* package34. These functions take the time-series of manual dendrometer band measurements and return maximum-likelihood optimized values of the above five parameters that best predict DBH for each day of year. An advantage of this approach is that short-term shrinkage and swelling associated with rain events34,58 and measurement errors show up as residual variation and do not unduly influence the parameters of interest. Having fit the model for each band-year of data, we then modeled DBH using these optimal parameter values in our logistic growth model and extracted the intra-annual growth variables of interest (Fig. 1).

After fitting the growth model, we removed tree-years with poor fits. Models were judged to be poorly fit if modeled growth parameters were outliers, which were commonly indicative of unrealistic fits (e.g., growth occurring outside the growing season or over a very short period) and underlain by very slow tree growth or poor data records that passed the initial screening (described above). Modeled fits for tree-years were removed under two conditions: (1) *gmax* was standard deviations away from the mean for each site-xylem architecture group combination (SCBI = 3, Harvard Forest = 11); (2) timing variables (*DOYip*, *DOY25*, *DOY50*, *DOY75*) were standard deviations away from the means for their site, xylem architecture group, and year (SCBI = 74, Harvard Forest = 101). At both sites the tree-years removed through this method were proportional to the original sample size, indicating that no species or size class was disproportionately removed compared to others. This process was repeated using 2 and 3 standard deviations as the cutoff for defining outliers, yielding qualitatively similar results.

Canopy foliage phenology data for the years 2001-2018 were extracted for SCBI and Harvard Forest from the MCD12Q2 V6 Land Cover Dynamics product (a.k.a. MODIS Global Vegetation Phenology product)59 via Google Earth Engine. For each year at each site, we extracted data from the pixel containing the center of each forest plot (resolution of 500m). Using the daily MODIS 2-band Enhanced Vegetation Index data (EVI2), the product yields the timing of phenometrics (vegetation phenology) over each year, including timing of greenup, midgreenup, peak, and senescence as used in this study. Data points were included in the analysis if they were flagged as “good” or “best” quality.

For the dendrometer band and leaf phenology analyses, climate data corresponding to the measurement periods were obtained from local weather stations at each focal site. For SCBI, weather data were obtained from a meteorological tower adjacent to the ForestGEO plot, via the ForestGEO Climate Data Portal v1.0 (<https://forestgeo.github.io/Climate/>)60. The R package *climpact* (see www.climpact-sci.org)61 was used to plot temperatures for visual inspection and to identify readings that were >3 standard deviations away from yearly means, which were labeled as outliers and removed from the dataset. Gaps in the SCBI meteorological tower data were subsequently filled using temperature readings obtained from a National Center for Environmental Information (NCEI) weather station located in Front Royal, Virginia (<https://www.ncdc.noaa.gov/cdo-web/datasets/GHCND/stations/GHCND:USC00443229/detail>). Daily temperature records for Harvard Forest, which had already been gap-filled based on other local records, were obtained from the Harvard Forest weather station62,63. For each site, we used records of daily maximum (*Tmax*) and minimum temperatures (*Tmin*). Standardized Precipitation Evapotranspiration Index (SPEI)57 values were obtained from the ForestGEO Climate Data Portal v1.0 (<https://forestgeo.github.io/Climate/>)60,64,65.

The critical temperature window (CTW, Fig. 1), defined as the period over which *Tmax* was most strongly correlated with *DOY25*, was determined using the R package *climwin*66. This package tests the correlation between one or more predictor climate variable and a biological outcome variable over all consecutive time windows within a specified time-frame. It does so by reporting the correlation and , the difference in Akaike Information Criterion corrected for small sample size relative to a null model for each window. Here, we tested for correlation between temperature predictor variables (*Tmax*, *Tmin*) and biological outcome variable *DOY25* over the time-frame from January 1 to the mean *DOY25* for the species group (by xylem porosity) and site (Extended Data Table 2). The time period yielding the lowest was selected as the CTW. To avoid spurious correlations that could occur using temperature data at the daily resolution, we ran this analysis with weekly resolution, using temperatures averaged over weekly time periods. Because *Tmax* proved to have a generally stronger influence over *DOY25* and other growth parameters, we focused on this variable in our ultimate model, as opposed to *Tmin*. We defined CTW for *DOY25*, as opposed to other parameters describing the timing of growth, because spring temperatures should have the most direct influence on this variable.

To ensure that patterns were robust under an alternative definition of CTW, and to parallel the monthly time windows used in our tree-ring analysis (detailed below; Fig. 3, Extended Data Figure 6-7), we also ran analyses where we fixed the CTW identified by *climwin* to be the month with the most days in the CTW (Extended Data Table 2) each critical window. The months identified were March and April for ring- and diffuse-porous species at SCBI, respectively, and April and May for ring- and diffuse-porous species at Harvard Forest, respectively.

Correlation between the dendrometer band-derived growth parameters (*DOY25*, *DOY50*, *DOY75*, *Lpgs*, *gmax*, and , Fig. 1) and CTW *Tmax* (at weekly or monthly resolution, as described above) were assessed using a linear mixed model in a hierarchical Bayesian framework. Analyses were run for both *Tmax* and *Tmin*, with qualitatively similar results, but we present only results for *Tmax*, which had overall stronger correlation with growth parameters. Mixed effects models were used to test the response of growth parameters to fixed effects of xylem porosity and mean *Tmax* (or *Tmin*) during the CTW, along with random effects of species and of individual tree. We ran separate models for each site, and for the response of all growth parameters to *Tmax* (or *Tmin*). This mixed-effect model was run within a hierarchical Bayesian framework and fit using the rstanarm R interface to the Stan programming language67,68. In all cases unless otherwise specified, all prior distributions are set to be the weakly informative defaults.

To rule out the possibility that observed patterns were strongly influenced by summer drought, we examined the relationship between spring temperatures and summer SPEI indeces. Linear models were run with 4-, 6-, and 12-month SPEI values of June, July, and August vs April *Tmax* to determine if warm spring temperatures were associated with greater summer drought stress in our data set. No significant correlations were found (all p>0.05).

## Tree-ring analysis

We analyzed tree-ring records for 108 sites, including our focal sites. All cores had been previously collected, cross-dated, and measured using standard collection and processing methodologies69.

Dominant tree species were cored at both SCBI33,53 and Harvard Forest4,70,71 following sampling designs that covered a broad range of DBH. We analyzed records for the ring- and diffuse- porous species at each site (Extended Data Table 1), but excluded semi-ring porous species (e.g., *Juglans nigra* L. at SCBI) and conifers (e.g., *Tsuga canadensis* at Harvard Forest). We studied a total of 976 cores which included 12 species at SCBI and 4 species at Harvard Forest (Extended Data Table 1).

The tree-ring records from our focal sites were complemented with a much larger collection spanning 106 deciduous and mixed forest sites in Eastern North America32,72. Again, records were limited to broadleaf deciduous species with clearly defined xylem porosity (*i.e.*, excluding semi-ring porous).

For each species-site combination, we converted tree-ring records into the dimensionless RWI to emphasize interannual variability associated with climate73. A 2/3rds *n* spline was applied to each core using ARSTAN to produce standardized ring-width series; *n* is the number of years in each series73,74. An adaptive power transformation, a process that also stabilises the variance over time75, was used to minimize the influence of outliers in all series. Low series replication, often in the earliest portions of a chronology collection, can also inflate the variance of tree-ring records76. The 1/3rds spline method was chosen when replication in the inner portion of each chronology (ca. inner 30–50 yr of each record depending on full chronology length) was less than three trees. When replication was greater than n = 3 trees, we used the average correlation between raw ring-width series (rbar) method. The robust biweight mean chronology (RWI) for each species-site combination was calculated from the ring-width indices following variance stabilisation74. We defined chronology start year (Extended Data Table 1) as the year where subsample signal strength (SSS) passed a threshold of SSS = 0.8, or where 80% of the population signal was captured in the chronology.

For the analysis of correlation between RWI and climate variables, we obtained monthly *Tmax* and *Tmin* data for 1901-2019 from CRU v.4.04.56 Correlations between monthly climate and RWI were assessed in R **v 4.0**77 using the packages *dplR*78 and *bootRes*79 to assess correlations, provide bootstrapped confidence intervals for these relationships, and create summary figures (Fig. 3, Extended Data Figures 6-7) following the methods of Ref.80. Our analysis focused on assessing correlations of RWI to months spanning from January through September of the current year (presented in Fig. 3, Extended Data Figure 6). To test for potential lag effects of spring temperatures on growth the following year, we also ran a version of the analysis extending back to include climate of every month of the previous year (Extended Data Figure 7). Correlations and significance levels for months March-August are given in SI Table 1.

We used a multivariate model to test for joint effects of April and summer *Tmax* on RWI. We focused on April to represent spring temperatures because it was the month with greatest overall alignment with the CTW’s identified in the dendrometer band analysis and had the highest rate of positive correlations with RWI (Extended Data Table 3). We began by testing univariate correlations of *Tmax* over three summer windows: June, June-July, and May-August. Having determined that, among these, June-July explained the most variation, we then analyzed the joint effects of April *Tmax* and June-July *Tmax* on RWI for each chronology independently using the base lm() function in R. Slopes and p-values for each chronology are given in SI Table 1. Although some models may have benefited from data transformations, we determined that assumptions of normality and homoscedasticity were sufficiently met for the purposes of this analysis.

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# Author Contributions

Cameron Dow and Kristina J. Anderson-Teixeira conceived the ideas and designed the study; Cameron Dow, Loïc D’Orangeville, Erika B. Gonzalez-Akre, Ryan Helcoski, Grant L. Harley, Justin T. Maxwell, Ian R. McGregor, William McShea, Neil Pederson, Alan J. Tepley, and Kristina J. Anderson-Teixeira collected or oversaw collection of data; Cameron Dow, Albert Y. Kim, Valentine Herrmann, Justin T. Maxwell, Ian R. McGregor, Sean McMahon analyzed the data or provided analytical tools; Cameron Dow and Kristina J. Anderson-Teixeira led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

# Data Availability Statement

The datasets generated and analysed during the current study are available via GitHub in the *growth\_phenology* repository of the ForestGEO Ecosystems & Climate Lab @ SCBI, (<https://github.com/EcoClimLab/growth_phenology>) and archived in Zenodo (DOI *[TBD]*). Master versions of the dendrometer band data are available for SCBI via GitHub in the *Dendrobands* repository of the Smithsonian Conservation Biology Institute ForestGEO plot (<https://github.com/SCBI-ForestGEO/Dendrobands>), which is archived in Zenodo (DOI 10.5281/zenodo.5551143), and for Harvard Forest via the Harvard Forest Data Archive (<https://harvardforest1.fas.harvard.edu/exist/apps/datasets/showData.html?id=HF149>). Weather data for SCBI were obtained from the ForestGEO Climate Data Portal v1.0 (<https://github.com/forestgeo/Climate/tree/master/Climate_Data/Met_Stations/SCBI>), which is archived in Zenodo (DOI: 10.5281/zenodo.3958215), and the National Center for Environmental Information (NCEI) weather station located in Front Royal, Virginia (<https://www.ncdc.noaa.gov/cdo-web/datasets/GHCND/stations/GHCND:USC00443229/detail>), downloaded on [DATE]. Weather data for Harvard Forest are available through the Harvard Forest Data Archive (<https://harvardforest1.fas.harvard.edu/exist/apps/datasets/showData.html?id=HF001> AND <https://harvardforest1.fas.harvard.edu/exist/apps/datasets/showData.html?id=HF000>). Climate data were obtained from CRU v.4.04 via the ForestGEO Climate Data Portal v1.0 (<https://github.com/forestgeo/Climate/tree/master/Climate_Data/CRU>), which is archived in Zenodo (DOI: 10.5281/zenodo.3958215). The Standardised Precipitation-Evapotranspiration Index was obtained from the ForestGEO Climate Data Portal v1.0 (<https://github.com/forestgeo/Climate/tree/master/Climate_Data/SPEI>), which is archived in Zenodo (DOI: 10.5281/zenodo.3958215). Canopy foliage phenology data were extracted from the MCD12Q2 V6 Land Cover Dynamics product (a.k.a. MODIS Global Vegetation Phenology product) via Google Earth Engine (<https://developers.google.com/earth-engine/datasets/catalog/MODIS_006_MCD12Q2#description>). Original tree cores are archived at the institutions of various members of the author team and will be made available upon reasonable request.

# Code Availability Statement

Data were analysed in the open source statistical software R (version 4.0). We used packages *climwin* v.1.2.3 (<https://cran.r-project.org/web/packages/climwin/index.html>), *dplR* v.1.0.2, and *bootRes* v1.2.4, *rstanarm* v.2.21.1, and functions from *Rdendrom* (<https://github.com/seanmcm/RDendrom/>). We used *climpact* software v.1.2.8 (see www.climpact-sci.org). All custom code is available through the EcoClimlab GitHub repository (<https://github.com/EcoClimLab/growth_phenology>) and archived in Zenodo (DOI: *[TBD]*).

# Additional Information

**Supplementary Information** is available for this paper.

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