**Title:** Using tree-ring records to simultaneously characterize the influence of tree size and climate drivers on annual growth

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# Abstract

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1. Tree rings provide a valuable long-term record for understanding how climate shapes forest productivity. However, traditional analysis methods aggregate growth records of multiple trees into residual chronologies, and therefore cannot simultaneously account for the effects of climate, tree size, and slowly changing environmental drivers. This has limited the potential to use tree-rings to understand forest productivity, its climate sensitivity, and its global change responses.
2. Here, we develop a new method to simultaneously model non-linear effects of principle climate drivers and reconstructed tree diameter (). Specifically, after identifying the most important climate drivers and theirtime window of influence, we use generalized least squares models to model growth while accounting for the temporal autocorrelation inherent to each individual tree’s growth. We apply this method to tree-ring data from 3879 trees representing 41 species at ten globally distributed sites spanning a wide range of forest types.
3. Our analysis identified similar climate drivers operating over similar time windows to those obtained via traditional methods, but revealed that non-linear responses to climate variables were common. Growth rates–expressed as ring widths, basal area increments, or biomass increments–varied non-linearly with . The relative importance of versus climate varied across sites, and interactions between and climate were prevalent (*~50%* of cases tested). After accounting for , growth rate varied directionally over time in most species– declining in most (#%).
4. Our method provides a rigorous analytical framework for statistically modeling tree growth responses to the most important climate drivers, , and year in nonlinear models. The need for such an approach is highlighted by our findings that nonlinear growth responses to climate variables are common, that growth rates vary nonlinearly with , that significant - climate interactions are common, and that growth rates often change over time. By providing a framework for such analyses, our approach opens the door for using tree-rings to improve our understanding of forest responses to climate change.

**Keywords**: climate sensitivity; diameter; environmental change; Forest Global Earth Observatory (ForestGEO); generalized least squares; nonlinear; tree-ring

# Introduction

**Tree rings provide a long-term record of annual growth increments that is invaluable for understanding forests in an era of global change.** Spanning time scales of decades to centuries or even millennia, they provide by far the most robust method for characterization of the interannual climate sensitivity of tree growth (Fritts, 1976) and how it is changing (e.g., Sniderhan & Baltzer, 2016; Maxwell et al., 2016). Combined with forest censuses, they can be used to estimate forest woody productivity (; Graumlich et al., 1989; Teets, Fraver, Hollinger, et al., 2018) and its climate sensitivity (Helcoski et al., 2019; Klesse et al., 2018; Teets, Fraver, Weiskittel, et al., 2018). *other global change drivers* This information is critical to predicting forest responses to climate change, and thereby reducing the enormous uncertainty surrounding future contributions of Earth’s forests to the global carbon cycle (Friedlingstein et al., 2006). Yet, collection and analysis of dendrochronological records has been traditionally been optimized to detect climate signals rather than to predict forest productivity, its climate sensitivity, and how it may be changing (Cherubini et al., 1998; Klesse et al., 2018; Nehrbass-Ahles et al., 2014). As a result, prevailing approaches hold a number of limitations for using tree-rings to address pressing questions concerning forest productivity in the current era of rapid environmental change.

**Dendrochronological methods to characterize the climate sensitivity of tree growth have been optimized to obtain the strongest possible climate signal for climate reconstructions, but face limitations when it comes to characterizing the climate sensitivity of individual trees or .** Traditional methods begin by fitting a function (commonly a spline) to the growth record captured by each core, extracting residuals around the long-term trends, and then standardizing and average the residuals across cores to form a species-level ring-width index chronology (*DENDRO\_REFS*). Climate signals are then identified by examining month-by-month or seasonal correlations of the ring-width index chronology to one or more climate variables over the current year and, typically, previous year (e.g., Fritts, 1976; Meko et al., 2011; Zang & Biondi, 2015). Following identification of the top climate driver(s), statistical models describing their relationships to tree growth can be used for applications such as climate reconstruction (*DENDRO\_REFS*) or projection of tree growth responses to climate change (e.g., Charney et al., 2016). An important caveat for the latter, however, is that the slopes of correlations between climate variables and ring-width index chronologies are not identical to the mean sensitivity of individuals within the population, as the process of building species chronologies fundamentally alters and obfuscates individual-level responses (*REF-NEIL?*). Although population-level climate responses have been approximated based on climate sensitives derived from species chronologies (e.g., Charney et al., 2016; Helcoski et al., 2019), the removal of individual-level variation prior to analysis of climate sensitivity limits potential for using species chronologies to characterize the climate sensitivity of . In particular, analysis of species-level chronologies does not allow characterization of known variation in climate sensitivity in relation to tree size (discussed below), canopy position, or microhabitat (e.g., Bennett et al., 2015; McGregor et al., 2020).

**Dendrochronological studies most commonly focus on linear climate responses to single climate drivers and the settings in which these occur, thereby missing nonlinearities and additive or interactive climate effects known to be widespread within forest settings.** Nonlinearities in climate sensitivities of tree metabolism and growth have been observed across a wide range spatio-temporal scales. Over time frames of seconds to days, photosynthesis and respiration display a unimodal relationships to temporal variation in temperature (REFS), typically peaking at temperatures *reflective of the environment to which the organism is acclimated (Kumarathunge et al., 2019)*. Across broad geographical climate gradients, annual forest productivity generally increases with temperature, precipitation, and potential evapotranspiration () up to a point, after which it plateaus or decreases (Banbury Morgan et al., n.d.; Sullivan et al., 2020). Filling a critical gap between short-term physiological responses and the global gradients representing millennia of community assembly and species adaptation, the annual growth records of tree-rings capture tree growth responses to interannual climatic variation. Yet, because non-linearities are very problematic for reconstructing climate variables (Esper & Frank, 2009), systems exhibiting these are typically avoided–e.g., by sampling climate-limited forest boundaries, and analysis methods are designed around first-order linear growth-climate relationships (Fritts, 1976 **??**). Dendrochronological studies allowing for nonlinear or threshold responses of tree growth to climate are less common (Cook & Johnson, 1989; Tolwinski-Ward et al., 2013; Tumajer et al., 2017; Woodhouse, 1999), and we therefore know little about the nonlinearities in growth responses to interannual variation in climate that occur for trees within forest settings. Furthermore, tree-ring studies do not commonly consider the additive or interactive effects of climate variables on annual growth (but see Meko et al., 2011; Foster et al., 2016). Temperature and moisture are known to jointly shape tree growth (Beedlow et al., 2013; Foster et al., 2016) and forest productivity (e.g., Alexander et al., 2018; Banbury Morgan et al., n.d.), but their influence may occur over different time windows.

**Tree diameter at breast height () is closely correlated with numerous variables affecting tree growth rate [e.g., height, crown size and position, root mass; REF] and therefore is one of the most important variables influencing growth (e.g., Muller-Landau et al., 2006; Foster et al., 2016) and its climate sensitivity (e.g., Bennett et al., 2015; McGregor et al., 2020).** However, for dendrochronological studies aimed at deciphering climate signals, is not typically a variable of interest, and its influence is removed through detrending (Cook & Peters, 1997). Moreover, many studies constrain sampling to only larger size classes. While convenient for identifying climate signals [Fritz 1976?(DENDRO\_REFS)], this approach is not optimal for subsequent inference of the climate sensitivity of forest productivity. Although climate correlations can be transformed to climate sensitivity (*sensu* Charney et al., 2016) and scaled to characterize the climate sensitivity of based on the scaling of with (Helcoski et al., 2019), they cannot be used to characterize known interactive effects of and climate on tree growth. For example, larger trees tend to be relatively more sensitive to drought (Bennett et al., 2015; Gillerot et al., 2020; McGregor et al., 2020), and smaller trees can be more sensitive to temperature (*Rollinson et al. in review*). However, the removal of signals via detrending makes it impossible to account for such size differences in climate sensitivity. To use tree-rings to predict tree growth, , and forest dynamics, we need models that include and its potential climate interactions.

**Characterizing how tree growth and forest productivity are responding to global change (slowly-changing environmental drivers) is very challenging and uncertain.**

* directional climate change (as opposed to variation), CO2, and atmospheric deposition are all potentially influencing tree growth.
* at the same time, stand dynamics influence growth; many forests are secondary, and ANPP\_woody may decline as stands age
* a variety of methods are used to account for simultaneous changes in tree size, including… (DENDRO\_REFS).
* One commonly applied approach is to assume that is fundamentally independent of size (DENDRO\_REFS).
* None of these methods is fully satisfactory, being subject to various sampling and analysis biases (Cherubini et al., 1998; Nehrbass-Ahles et al., 2014), leaving great uncertainty as to what the tree-ring record can tell us about the impact of rising CO2 (Walker et al., 2020).
* It is necessary to *simultaneously* account for the influences of changing tree size and environmental drivers.

**Here, we develop a new method that allows simultaneous consideration of the effects of principle climate drivers, tree size and year on annual tree growth.** This allows us to ask: (1) What are the most important climate drivers of annual growth, and over which time windows? (2) What is the shape of the relationship between annual growth and climate drivers? (3) How do , , and aboveground biomass increments () vary with ? (4) How do climate drivers and additively and interactively shape growth? (5) How have growth rates changed through time?

# Materials and Methods

## Data sources and preparation

We analyzed previously collected tree-ring data from ten sites ranging from 9.15 to 61.30 N latitude and representing a wide range of forest and tree types: tropical broadleaf deciduous and evergreen, temperate broadleaf deciduous and needleleaf evergreen, and boreal needleleaf evergreen (Tables 1, S1, S2). Nine of these sites (exception: LT) are large forest dynamics plots of the Forest Global Earth Observatory (ForestGEO; Anderson-Teixeira, Davies, et al., 2015). Trees of species represented within the ForestGEO plots were cored within the plot (n=#) and/or in the vicinity (n=#; max distance: # km), following a variety of sampling protocols designed to meet the varied objectives of the original studies (Tables S1, S3). In using this diversity of data sources, we ensured that our approach was able to handle challenges presented by varying methodologies and forest types.

**Table 1 | Sites included in this analysis**. Here and throughout, sites are ordered by descending mean annual temperature. Additional site information is provided in Table S1, and species and their sample sizes are detailed in Tables S2-S3. 

All tree cores were measured and cross-dated by the original researchers using standard dendrochronological practices. From among the full set of *#* original records, we excluded cores for which we detected errors (e.g., labeling inconsistencies, obvious dating errors) that could not be resolved before finalizing the analysis (n=*#*). We also excluded records that had to be excluded due to insufficient sample size or anomalous growth patterns, including (1) species with <7 cores, (2) cores with <30 years of record, (3) contiguous portions of cores containing large outliers ( > mean plus 5 x SD of for the entire core), and (4) the final 20 years prior to death of trees cored dead. The final criteria was implemented to avoid periods of growth decline and potentially altered climate sensitivity prior to death (Cailleret et al., 2017; DeSoto et al., 2020). From analyses including (see below), we further excluded (1) trees for which we lacked data required to reconstruct , (2) trees for which there was a significant inconsistency between measured and the sum of ’s across the core (Appendix S2), and (3) poorly represented edges of the range, starting where reconstructed (see below) was represented by <3 conspecific trees. In total, this resulted in inclusion of *#* cores, 4243 of which could be included in analyses with (Table S3).

For each year in the tree-ring records, we reconstructed , as detailed in Appendix S2. We used allometric equations between and bark thickness to account for changes in bark thickness as the tree grew (Appendix S2; Tables S2, S4).

Once had been reconstructed, we used biomass allometries to estimate the corresponding aboveground biomass and diameter to area equation to get the corresponding basal area. We then calculated aboveground biomass growth increments () as [] and basal area increment () as []. Biomass allometries for temperate and tropical sites were calculated using the R packages *allo-db* (Gonzalez-Akre et al. in review) and *biomass* (Réjou-Méchain et al., 2017), respectively.

Monthly climate data for 1901-2019 were obtained from CRU v.4.04 (Harris et al., 2014, 2020), and in a few cases corrected based on more local records (Appendix S3). Variables considered here included average daily minimum, maximum, and mean temperatures (, , , respectively); precipitation (); and, when deemed reliable (Appendix S3), potential evapotranspiration () and precipitation day frequency (). All ForestGEO climate records used here are archived in the ForestGEO Climate Data Portal, v1.0 (Anderson-Teixeira et al., 2020).

## Analysis methods

Our analysis consisted of two main steps: (1) identification of the most important climate drivers and the time window over which they operate, and (2) combining and climate drivers into a multivariate model (Fig. 1). The analysis was run separately for each site and each response variable (, , or ).



**Figure 1 | DRAFT Schematic illustrating our analysis process.** This analysis is conducted separately for each site.

### Climate variable selection

**We used the *climwin* package in R (van de Pol et al., 2016) to identify the most important climate driver and the time window over which its effect was strongest for each of two categories of variables: a temperature group (, , , and ) and a precipitation group (, ).** To remove low-frequency variation that most likely represents responses to non-climatic drivers (*e.g.*, growth and aging of the tree, change in competitive dynamics, atmospheric pollution), we detrended the response variables by using a generalized additive model (GAM) to fit a spline to individual growth records (, , or ) from each core, thereby producing residuals. (*How did you decide how flexible to make the spline?*) We then used *climwin* to identify the climate variables most strongly correlated to the residuals of , , or , specifying quadratic fits to allow for potential nonlinearities in the climate response. Within *climwin*, we specified a mixed effects model using species and core identity as random effects: residual growth index ~ [climate] + (1 | sp) + (1 | treeID). Here, for each permutation, climate specifies one of the climate drivers in the climate variable group, analyzed over one of all possible combinations of consecutive months over a 15 month period ending near the time of cessation of formation of each annual ring (Table S1). *Climwin* runs all potential models to select the best fit (lowest AIC), and does k-fold cross-validation in its computation of AIC to guard against over-fitting (van de Pol et al., 2016). For each group of candidate climate variables, we moved forward with the best variable over the time window identified by *climwin* as a candidate climate variable for the multivariate models.

We tested whether this process identified similar climate variable-month combinations as what would be identified using traditional methods for individual species, as detailed in Appendix S4. Furthermore, we explored alternate methods of climate variable selection for the two sites that have undergone the most rapid changes in climate and tree growth: SC, where rapidly rising temperatures are causing melting permafrost, summer moisture stress, and growth declines (Sniderhan & Baltzer, 2016), and LT, where increasingly warm drought has dramatically reduced growth (Williams et al., 2012). We ultimately determined that the method described above was reliable for the purposes of this analysis (Appendix S5).

### Combining drivers in GLS model

Having identified candidate climate drivers in temperature and precipitation variable groups, we next combined climate variables (all models) and (models with and its climate interactions) in a generalized least squares (GLS) model (Fig. 1). Before running the models, we checked for collinearity among the candidate variables using the *vifstep* function (**REF**) and removed any variable with a variance inflation factor > 3 (none required removal). Within the GLS models, our response variables were , , or . Rather than detrending these variables to produce residuals, the temporal autocorrelation of individual tree’s growth was accounted for by the specifying an autocorrelation structure of order 1, with as a continuous time covariate and as a grouping factor, in the GLS’s model specification. For each species independently, we ran every combination of the candidate climate variables and , including both first- and second-order terms of polynomial for each. For climate responses, we allowed concave-down fits, but ignored any concave-up fits on the basis that these are not expected biologically and, when identified in initial analyses, often appeared to be cases of over-fitting.

For models including interactive effects of climate and , we tested for interactions between first-order linear terms for climate variables and .

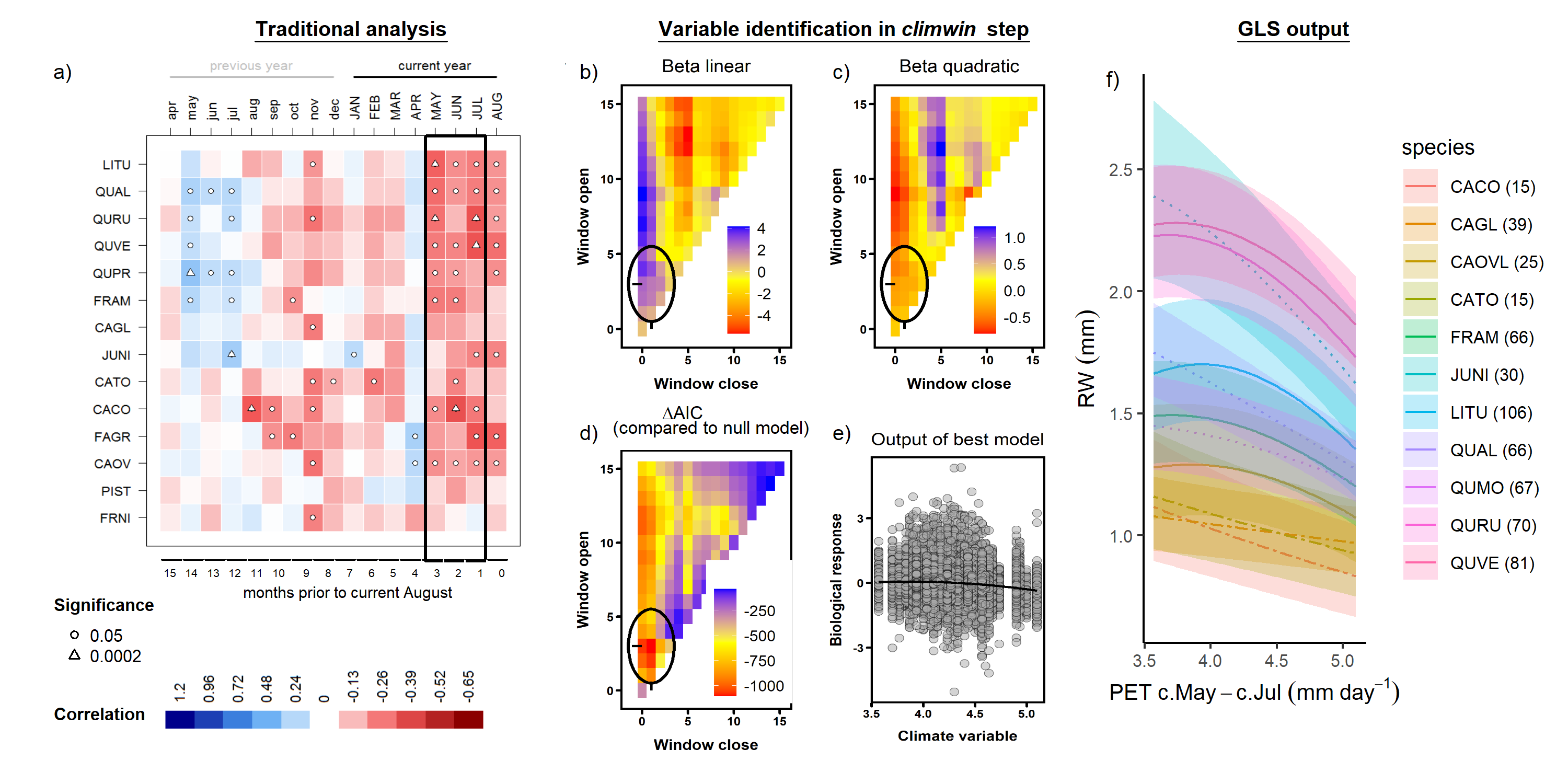
To test for effects, we limited the analysis of each species to years for which the range represented by at least 3 individuals spanned at least half the total range of that species, dropping species entirely if < 30 years met this criteria. We then ran models as described above, including a first-order linear effect of . To verify that GLS model trends for were real, as opposed to an artifact of inherent covariation between and within each core, we separately analyzed -growth relationships by decade (Appendix S6). For simplicity and consistency with previous literature, we present only the models with as the growth metric, noting that responses were similar across metrics.

Within each of three categories of models run (climate only, climate + , climate , climate + + ), we selected as the top model that with the lowest AIC.

# Results

## Climate sensitivity

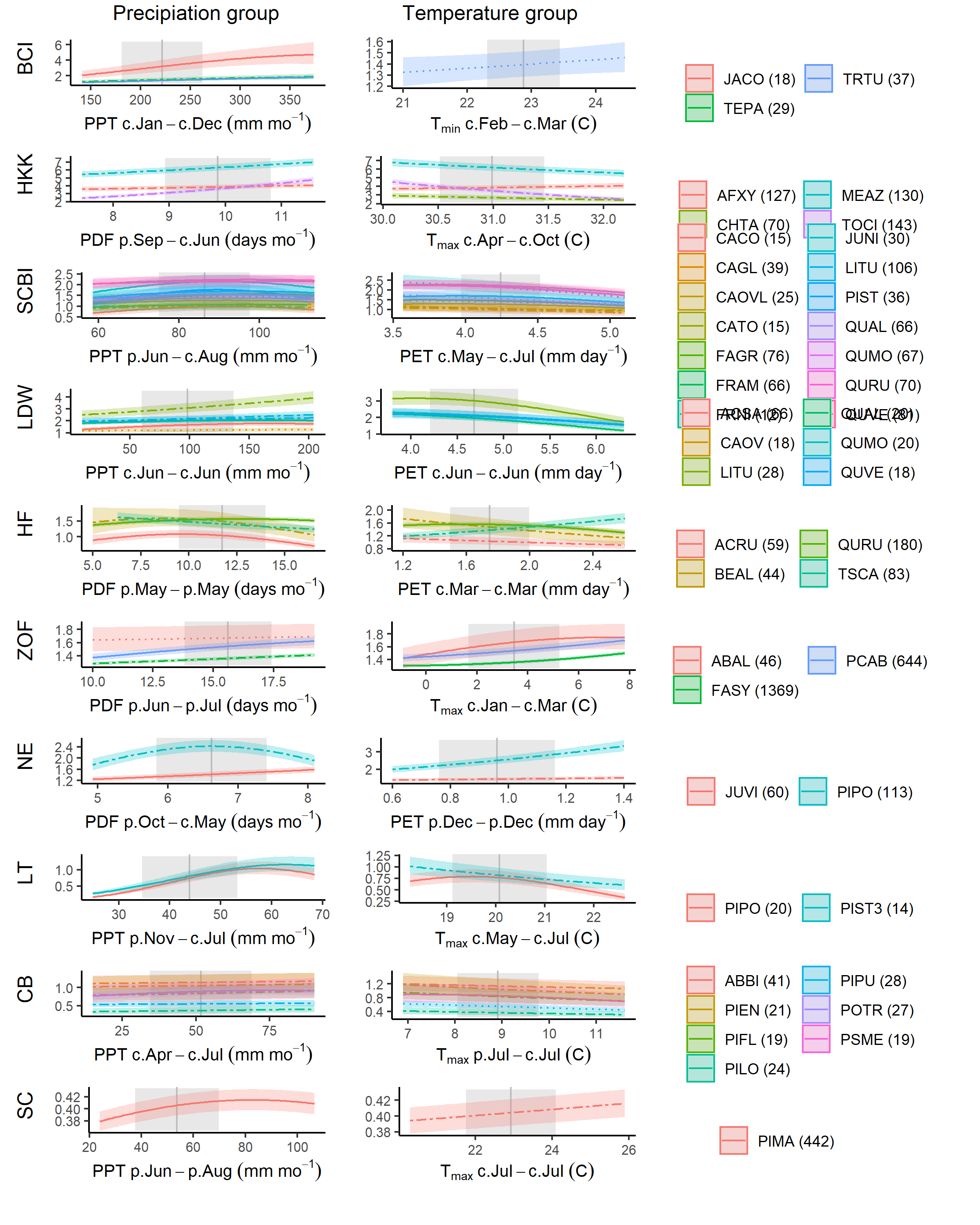
Using as the growth metric, our process identified similar climate drivers to those identified via traditional dendrochronological analysis methods (Figs. 2, S1-S4; Table S5; Appendix S4). While one-to-one correspondence of estimated climate coefficients was neither expected nor observed, estimates were correlated and rarely differed significantly (Appendix S4; S1-S4).



**Figure 2 | Example comparison of climate sensitivity derived via traditional methods (**a**) and our approach (**b-f**).** Example is for the sensitivity of 14 species at SCBI (codes given in Table S2) to potential evapotranspiration (). Panel (**a**) shows a matrix of Pearson correlations between ring-width index and monthly climate variables (using the chronologies of Helcoski et al. 2019). Black rectangle represents the period selected by *climwin* as the most influential window. Panels (**b-d**) give statistics for time windows tested in *climwin*, where window open and close indicate months prior to current August, and cells across the lower diaganol indicate single-month tests (akin to panel **a**). Panels (**b**) and (**c**) give values of linear and quadratic terms for each time window, and (**d**) gives the for each. The time window with the minimum (1-3 months prior to August, or May-July; black circles), was identified as the optimal window. Panel (**e**) shows the correlation of individual-level residuals to PET, with the function fit in *climwin*. Finally, panel (**f**) shows GLS model output, where was a candidate driver variable (along with ; not included in this model). Plotted are responses of species for which was included in the top model, with best-fit polynomials plotted with solid lines when both first- and second-order terms are significant, dashed lines when only one term is significant, and dotted lines when neither is significant. Transparent ribbons indicate 95% confidence intervals.

The three metrics of growth (, , and ) exhibited similar strength of correlation and direction of response to climate variables across the range of potential time windows, but the optimal time window or even the top climate variable sometimes differed (Figs. S5-S7). In 7 of 20 cases, both the optimal climate variable and time window were identical across growth metrics (e.g., Fig. S5). In 11 cases, *climwin* identified the same climate variable but different (often overlapping) time windows (e.g., Fig. S6). Finally, in two cases of variables that had only weak effects and mixed responses among species in the final models (temperature variable group at HKK, precipitation variable group at HF; Figs. 3, S10, S13), *climwin* identified different climate variables and different time windows (e.g., Fig. S8). Henceforth, unless otherwise noted, we focus on the climate sensitivities identified with as the growth metric and for the full set of cores (*i.e.*, including those for which could not be reconstructed).

Within the context of the GLS model, which tested for first- and negative second- order linear effects of both a precipitation and a temperature variable, both a precipitation and a temperature variable were included in the top model for 80% of site-species combinations (n=37 of 46; Fig. 3). There were eight site-species combinations for which only a precipitation term was significant (2 at BCI, 3 at SCBI, 2 at LDW, and 1 at CB), one for which only a temperature term was significant (CHTA at HKK), and none with no significant climate responses. Precipitation and temperature variables were rarely influential over the same time window (exception: LDW). Below, we summarize the precipitation and temperature variables included in these models and their direction of response.



**Figure 3 | Species-level responses of to climwin-selected variables in precipitation and temperature variable groups.** *Climwin*-selected climate variables are coded on the x-axes as the climate variable name followed by the range of months (p=previous year, c=current year) over which it is most influential. For each species (color-coded as in Fig. 4), relationships are plotted if included in top model. For each relationship shown, other terms in the model are held constant at their median. Best-fit polynomials are plotted with solid lines when both first- and second-order terms are significant (t-test’s p-value <0.05), dashed lines when only one term is significant, and dotted lines when neither is significant. Transparent ribbons indicate 95% confidence intervals. Vertical grey lines indicate the long-term mean for the climate variable, shading indicates 1 SD. (THIS FIGURE WILL PROBABLY CHANGED INTO A 4COL X 5 ROW MATIX, DROPPING SPECIES KEY, WHICH CAN BE SEEN IN OTHER FIGURES)

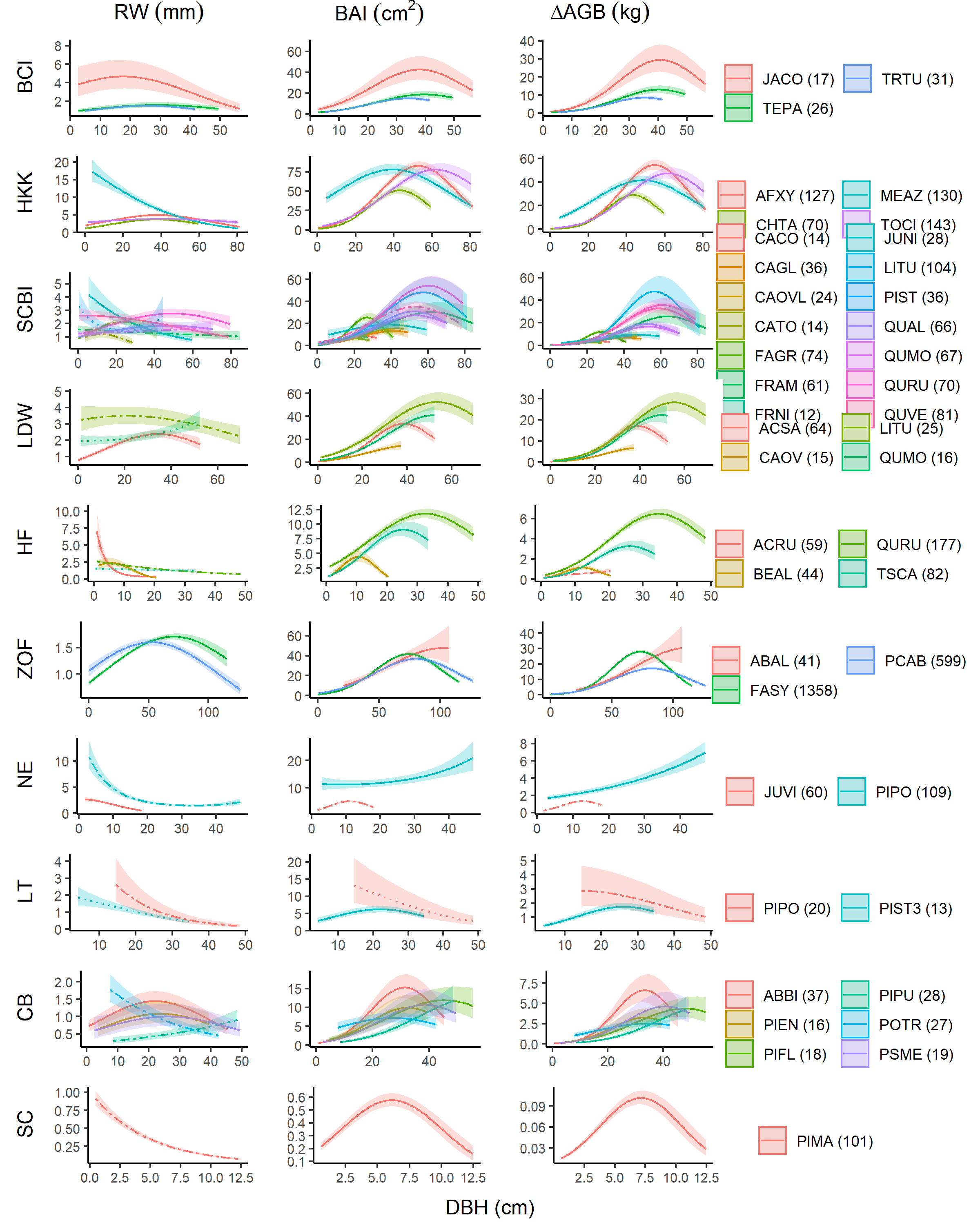
Responses to precipitation amount () and frequency () were included in the best model for all but one species, and were predominantly positive (Fig. 3). and were each identified as the top variable in four of the eight sites with both variables available, while was the only option at two (LT and CB). Optimal time windows most commonly coincided at least partially with the months of most active growth in the current year (Fig. 3; Table S1): wet seasons in the tropics (BCI and HKK) or late spring/ early summer in the extratropics (n= 5 of 8). In the tropics, the long time windows over which precipitation was influential (12 mo at BCI, 9 mo at HKK) also included the majority (BCI) or all (HKK) of the dry season. At three extratropical sites (LDW, NIO, and CB), the most influential windows were limited to the current spring and early summer, whereas optimal windows at two sites extended back to the previous fall (LT) or summer (SCBI). Finally, at three sites (HF, ZOF, and SC), precipitation of the previous growing season was the most influential variable. Responses to or were predominantly positive, with positive first-order linear terms for all but two species (*Tsuga canadensis* at HF and *Betula papyrifera* at NIO; Fig. 3). Negative second-order terms were commonly included in the best model (*# of #* with positive first-order terms), generally resulting in a deceleration or decline at the highest levels of precipitation, but occasionally producing a unimodal (e.g., several species at SCBI) or predominantly negative response (e.g., BEAL at HF; Fig. 3). At the riparian site (NIO), for which streamflow was included as a candidate variable in the precipitation group, May was selected as the strongest driver but had a modest negative effect on growth, indicating that water availability was not a significant limitation for *Betula papyrifera* at this site.

A temperature variable was included in the best model for all but eight site-species combinations, with predominantly negative responses (*#*% of species; Fig. 3). The most commonly selected variables within the temperature group were and , which were identified by *climwin* as the top temperature-related driver at five and three of the ten sites, respectively, noting that was not available for two sites. and were each identified as the top driver at only one site (NIO and BCI, respectively), noting that the effects of at BCI were only marginally significant (Fig. 3). Optimal time windows most commonly occurred during the peak growing season of the current year (n= 5 of 10 sites), but there were cases where optimal windows occurred during the preceding dry season (BCI), late winter/early spring (HF, ZOF), the previous growing season (NIO), or a 13-month window extending from past to current growing season (CB). Within the tropics, there was minimal effect of temperature at BCI and a negative effect of wet season for three of four species at HKK. For temperate sites with optimal time windows covering the current and/or past growing season, responses were universally negative (i.e., negative first-order linear or unimodal, peaking at temperatures lower than the long-term mean). In contrast, there were positive effects of Jan-March for all three species at ZOF and of March for *Tsuga Canadensis* at HF, the latter contrasting with a negative response of the other three species at HF (Fig. 3). At the highest-latitude site (SC), which has undergone rapid warming and permafrost melt, *Picea mariana* responded positively (but with wide 95% CI on the slope) to temperature over the full analysis period (1903-2013); however, responses were predominately positive prior to 1970 and predominantly negative afterwards (Fig. **CREATE AN SI FIGURE!**).

## Influence of DBH

**All three growth metrics, , , and , varied with for most species at all sites (Fig. 4).** varied significantly with for 81% of species-site combinations (n= 34 of 42), and the majority of best models included a significant second-order linear term (n= 25, 22 of which were negative; Table **S#**). There was substantial variation in these trends, with patterns mixed across both forests and species within a single stand (Fig. 4). On one end of the spectrum, some species exhibited maximum at low , followed by fairly rapid declines in with increasing . Species following this pattern either had low to at most intermediate shade tolerance (e.g., *Melia azedarach* at HKK, *Juglans nigra* at SCBI, *Acer rubrum* at HF, *Betula papyrifera* at NIO; *Populous tremuloides* at CB; Table S2) and/or grew in relatively open stands (e.g., both species at LT, *Picea mariana* at SC; Fig. 4). At the other end of the spectrum, some species had low at small , increased to peak at intermediate , and subsequently declined. These included, but were not limited to, shade-tolerant species at sites where they presumably established under closed-canopy conditions (e.g., *Trichilia tuberculata* and *Tetragastris panamensis* at BCI; *Fagus* spp. at SCBI and Žofín, *Acer saccharum* at LDW, *Picea* spp. at Žofín and CC; Table S2).

**Trends in both and were far more consistent across sites and species, most commonly increasing to a peak at intermediate and then declining (Fig. 4).** Best models for included and for 41 of 42 species (exception: *Acer rubrum* at HF), with a positive coefficient for in 40 (exception: non-significant negative coefficient for *Pinus ponderosa* at LT, whose reconstructed DBH extended down to only 15cm within the time frame analyzed) and universally negative coefficients for . For , models were even more consistent, with the best models for 100% of species containing a positive coefficient for and a negative coefficient for .



**Figure 4 | Growth sensitivity to DBH: (a) , (b) , (c) .** Relationships for species are plotted when included in the top model. Other terms in the model are held constant at their median. Best-fit polynomials are plotted with solid lines when both first- and second-order terms are significant (t-test’s p-value <0.05), dashed lines when only one term is significant, and dotted lines when neither is significant. Transparent ribbons indicate 95% confidence intervals.

## Additive and interactive effects of climate and DBH

When a precipitation variable, a temperature variable, and were all included as candidate variables in the GLS models, typically all three were included in the top model, regardless of the growth metric used. Climate responses were generally similar to those described above for models without a term, although some of the weaker climate responses were not consistently included in top models (e.g., responses at BCI; Figs. 3, S9-S18). Responses to were as described above (Fig. 4).

In general, explained more variation in growth rates than did climate, but its relative importance varied across growth metrics and sites (Figs. S9-S18). The relative importance of tended to be least for , intermediate for , and highest for (e.g., at SCBI; Fig. S11). However, there were exceptions, particularly when decreased steeply with (e.g., LT; Fig. S16). The relative importance of climate was modest (but still significant) at sites including SCBI (Fig. S11), HF (Fig. S13), and SC (Fig. S18), and stronger at sites including BCI (Fig. S9) and LT (Fig. S16).

Interactive effects of climate and were found for 82 of the 219 (37%) species-variable combinations for which they could be tested. For precipitation variables, interactions were significant for 34% of interactions with as the growth metric and for 47% with as the growth metric (Table S6). The majority of these interactions were positive (77% for ; 67% for ), indicating that larger trees generally respond more positively (or less negatively) to precipitation or its frequency (Fig. 5). Among the exceptions to this pattern (n=3 for , 6 for ), only a minority (n=1 for , 3 for ) occurred in species responding positively to precipitation in the current growing season.

Temperature variable interactions were significant for 38% of cases with as the growth metric and for 29% with as the growth metric (Table S6). Directions of these interactions were mixed, with 5 of 13 significant interactions negative with as the growth metric and 6 of 10 significant interactions negative when was the growth metric. For both and , the majority of significant negative interactions (*i.e.*, more negative/ less positive response of larger trees to higher temperatures) occurred in the more water-limited forests (HKK, LT, CB), whereas positive interactions were more common in mesic forests (SCBI, HF, ZOF).

**figure on climate - DBH interactions? EFFECT SEEMS TO BE FAIRLY STRONG AT LT AND MAYBE SC (NEEDS UPDATING)** (*See* [*ISSUE #42 in ForestGEO-climate-sensitivity*](https://github.com/EcoClimLab/ForestGEO-climate-sensitivity/issues/42))

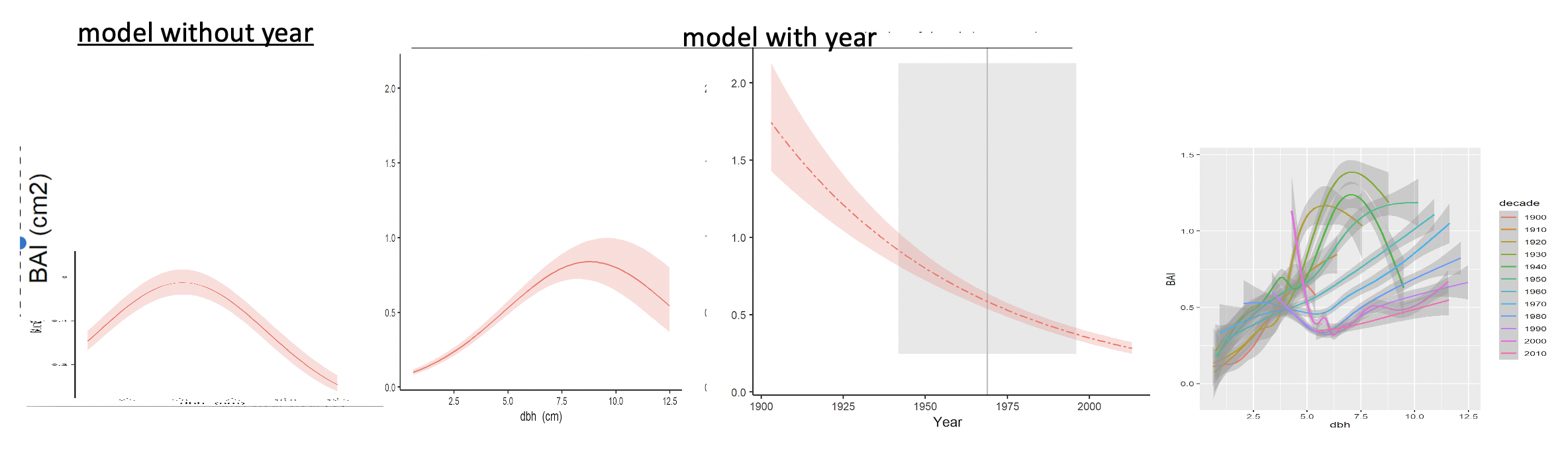
**Table 2. Summary of climate interactions and effects.**

**Table 2. Summary of climate interactions and effects.**

## Effects of year

*(tentative results. We’re not yet getting the constraints on scope right. It is messing up on POTR, for which only ~20 yrs of data get included.)*

There was a significant effect of year in the GLS models for 32 - 36 (depending on growth metric) of the 40 species- site combinations tested (Table S6), and these trends matched those observed in a separate analysis of -growth relationships by year (Appendix S6; **ADD SI FIGS**). In the majority of cases (91-94%, depending on growth metric), the growth trend over time was negative. Declines were particularly dramatic (**give some criteria**) for *all four species at Harvard Forest, PIPO at Little Tesuque,* ***POTR at Cedar Breaks****, and PIMA at Scotty Creek* (Fig. 6). In these cases, models without year predicted declines in growth at large DBH that should more properly be attributed to the effect of year (Fig. 6). Significant positive growth trends were observed for only three species, FASY at ZOF, PIPU and **POTR** at CB, and all were modest compared to the steep negative trends observed for some species. Growth rate was consistently independent of year for only four species: *Chukrasia tabularis* at HKK, *Fraxinus nigra* at SCBI, and *Picea engelmannii* and *Pinus flexilis* at CB.



\*\*Figure 6 | DRAFT FIGURE. GLS model with and without year, maybe decadal analysis plot. IT WOULD BE BEST TO COMBINE THE 2 DBH FIGURES (PANELS 1,2). CURRENT EXAMPLE IS JUST SCOTTY CREEK, BUT IT WOULD BE GOOD TO SHOW AT LEAST ONE OTHER.

# Discussion

**Our new tree-ring analysis method allows simultaneous consideration of the effects of objectively determined principle climate drivers, tree size, and year on annual growth (Fig. 1), yielding results that are consistent with those that would be obtained using conventional methods (Figs. 2, S1-S4; Table S5) and with our current understanding of forest dynamics.** Across diverse climates and forest types (Table 1), growth rates of 41 tree species generally responded positively to water availability (, , or )–at least up until the long-term mean– and negatively to temperature (usually or ), with the exception of several positive responses at times and in places where temperature was limiting (Fig. 3). Additive effects of water and temperature variables, usually over different time windows, occurred for most species, and nonlinear responses were common. Interactions between climate variables and not unusual (Table S6, Fig. 5), with larger trees tending to be more drought sensitive (REFS) *but less strongly affected by high temperatures (REFS)*. Growth rate–whether measured as , , or – varied nonlinearly with and was dependent upon species ecology in interaction with stand history and global change drivers (Figs. 4, 6). While none of these findings are biologically surprising, the simultaneous modeling of growth responses to climate, , and year offers a fuller picture of the drivers of tree growth in an era of global change.

## Climate sensitivity

*(corroboration of insight from conventional methods)*

**Our results are broadly consistent with those obtained by traditional methods, revealing similar climate sensitivities (Figs. 2, S1-S4; Table S5).** An advantage to our approach is that that the use of *climwin* allowed automated, objective selection of the strongest climate drivers and the time windows over which they were most influential. Note that the use of *climwin* itself is analytically convenient, but does not alter results relative to what would be obtained via a more conventional approach; numerous climate drivers and time windows can be compared without climwin (e.g., REFS), and *climwin* could also be used on residual chronologies (**AND WE DID THIS– ADD SI FIGURE AS EXAMPLE?**). Where our approach differs fundamentally from traditional methods is in analyzing climate sensitivity of the full sample of individual cores, as opposed to a residual chronology in which variance has been standardized and the individual cores have been averaged. The result is that our approach yields climate correlations with greater variance but lower standard error of slope estimates (Figs. S1-S4). Differences in slope between the two approaches are expected giving the methodological differences (Appendix S4), and were rarely statistically significant. (*add some discussion on why we expect different slopes?*) Another way in which the current analysis differed from conventional methods is that we pooled species when determining the top climate drivers (*climwin* step; Fig. 1). This decision was motivated by the expectation that differences in optimal climate windows across species in one site (e.g., Fig. 2) would be minimal compared to cross-site differences, and for the practical consideration that determining optimal climate windows for each species would be computationally intensive and challenging to present. However, species-specific climate sensitivity estimates could be optimized by fitting *climwin* individually be species. While our method sometimes may sometimes pick out different climate variables and time windows than would be identified via conventional methods, as a whole the identified drivers and directions of response are consistent with conventional methods (Table S5).

**While yielding broadly similar results to conventional analyses, our analysis yielded new insights that would not have been found with conventional methods.**

1. additive effects are prevalent, and time windows often differ (trees tend to be sensitive to water over longer time scales (makes sense– lags caused by soil moisture storage)
2. nonlinear effects are prevalent
3. DBH interactions –also potentially attributable to year– are common

## Size trends

**The diversity of growth trends in relation to observed here (Fig. 4) is largely attributable to species ecology and stand history (Fig. 4).** On one end of the spectrum, species that would have established in fairly open conditions–*i.e.*, shade-intolerant species and those at sites with more open canopies (e.g., LT, SC)– exhibited rapid initial growth followed by a roughly exponential decline. The most pronounced example of this pattern was *Melia azedarach* –a highly shade-intolerant species that establishes in the open (Baker & Bunyavejchewin, 2006) and was sampled opportunistically outside the ForestGEO plot at HKK (Vlam et al., 2014), where it presumably established under open conditions (*Baker 2005, Ecological monographs*). Such patterns are consistent with dendrochronology’s “textbook” patterns, which have been derived primarily from trees that established in high-light environments (*DENDRO\_REFS: See refs in Biondi and Qeadan 2008. Tree-Ring Research 64:81-96.; There are several earlier references in B&B 2006 describing this pattern.* ). On the other end of the spectrum, shade-tolerant species (e.g. *Fagus* at SCBI and Žofín) exhibited initially low, but increasing, . This pattern is consistent with patterns observed in stand-level census data from closed-canopy forests, including several in this analysis, where increases continuously with [Muller-Landau et al. (2006); Anderson-Teixeira, McGarvey, et al. (2015); Piponiot et al. in prep]. While the low community mean at small observed in closed-canopy forests is in large part driven by slow-growing small stems that will never enter the cohort of trees sampled by coring (e.g., 10cm DBH) (*see Cherubini et al. 1998*), increases in with have also been observed for most species at SCBI using the same tree-ring data set analyzed here, but comparing across individuals using only contemporary data (Helcoski et al., 2019). Thus, patterns of decreasing with are likely limited to open-grown trees or those establishing in gaps.  
– (*cite Sheil et al. 2017* [*Clark et al. 2007?*](https://esajournals-onlinelibrary-wiley-com.smithsonian.idm.oclc.org/doi/epdf/10.1890/06-1039.1)*;* [*Schleip et al. 2015*](https://onlinelibrary-wiley-com.smithsonian.idm.oclc.org/doi/abs/10.1002/env.2324)). – *from PB: I think the one thing that is very hard to take into account (and which you noted in bold at the start of the paragraph) is stand history. I worry about looking for/finding general patterns just on tree size, as that ignores the historical dynamics that might influence these patterns.*

Contrary to the finding that increases continuously with , which was derived from census data from globally distributed forests (Stephenson et al., 2014) and has also been observed in tree-rings (Foster et al., 2016), we found evidence of saturation or decline in the majority **(77%)** of species-site combinations analyzed. declines at high are presumably because trees are investing fixed C elsewhere–for example, reproduction.

Forrester (2021) clarifies that increases with size across census data, but often declines with size over the course of a tree’s life.

## Changing growth rates

Growth rates are changing directionally for most species/ sites.

Stand dynamics strongly affect stand structure and therefore tree diameter and growth trends.

*corroboration of existing evidence*

At HKK, Nock et al. (2011) observed decreases in BAI (by standardized size classes) over time

*new insight*

Analyses of CO2 effects reach inconsistent conclusions because of stand dynamics, sampling bias, analysis methods…

We believe our analysis methods to be robust,

Our sampling varies by sites, and sites analyzed have decent year x DBH coverage, but biases could remain (need to do some research on this, believe it’s mostly stand dynamics)

Main bias would be stand dynamics. This is probably the case at secondary forests (HF, SCBI…). Even within mature forests, light-demanding species that establish in gaps (JACO at BCI, MEAZ at HKK) would tend to experience an increasingly competitive environment.

In stands with no known stand-clearing disturbance within or shortly prior to the analysis time frame (ZOF?, NM?, CB, SC), trends would represent more gradual successional trends or responses to global change.

At NM and SC, rapid declines in growth make sense in light of rapid climate change. They also correspond to observations of high tree mortality rates.

At ZOF and CB, trends are more mixed…

(*conclusions*) Altogether, results obtained using our analysis method reveal a much richer picture of the factors influencing tree growth than has previously been possible. We find that growth is generally simultaneously influenced by temperature and precipitation over different time windows, that nonlinear climate responses and interactive effects of climate with are common, that growth–measured by any metric–almost universally varies with , and that growth of most species has been changing directionally in response to changing environment (stand successional status or global change). These findings go against many of the assumptions that traditional dendrochronology methods, which sample and analyze data in order to minimize such effects. However, from an ecological perspective, these effects are of great significance.

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## Future challenges (?)

*(still face a problem when future climate is outside of the range of values used to model the climate-growth relationship. )*

*(growth rate should respond strongly to a tree’s relative DBH within a site, which we don’t have going back in time/ disentangling DBH and year is tough)*

# Misc (old) content/ notes to integrate

**These results have important implications for using tree-rings to infer growth responses to slowly-changing environmental drivers, including climate, atmospheric CO2, and deposition of sulfur dioxide (SO2) and nitrogen oxides (NOx) (e.g., Mathias & Thomas, 2018).** The observed trends in and with (Fig. 4) imply that two of the most commonly used growth-trend detection methods (*clarify what this means*), conservative detrending and basal area correction (see Peters et al., 2015), are inappropriate. Specifically, conservative detrending, which applies stiff splines or mathematical functions (e.g., negative exponential) to remove trends in before analyzing residuals, would not be reliable across the diversity of - relationships observed here. Basal area correction – i.e., assuming that is fundamentally independent of tree size after the removal of the juvenile growth phase–is also problematic because shows a variety of trends with across large size classes. The most common pattern–an increase to a peak at intermediate sizes, followed by decrease–would imply that the basal area correction is most commonly biased towards finding positive trends for smaller trees and negative trends for larger trees. It is therefore not surprising that tree-ring studies examining the impact of rising CO2 on long-term growth growth trends reach inconsistent conclusions (Walker et al., 2020).

*Additive and interactive effects of climate and DBH*

**We show that DBH is a strong driver of growth (any metric) relative to climate and that climate sensitivity often varies with DBH– findings that have important implications for understanding changes in forest productivity in response to climate change.** The observed importance of as a driver of tree growth reinforces the concept that changes in forest structure/ demography are critical to changes in forest productivity (REFS; McDowell et al., 2020). The prevalence of interactive -climate effects reinforces the concepts that large trees tend to be disproportionately sensitive to drought (Bennett et al., 2015; McGregor et al., 2020) but less sensitive to high temperatures *(Rollinson et al. in review)*, implying that size should be considered in tree-ring analyses of climate sensitivity. (Hacket-Pain et al. (2016) show an interaction) However, the relatively strong importance of in no way negates the importance of climate, as its effect would dominate changes in productivity in stands with relatively constant size structure. Some studies have made a start at combining tree rings and forest census data to get at the climate sensitivity of whole-forest productivity (e.g., Helcoski et al., 2019), but have been limited in that they were not underlain by models of individual tree growth that simultaneously characterized the effects of tree size and climate, as we do here. Further work will be required to combine this model with forest census data in order to understand the climate sensitivity of whole-forest productivity.

All this points to the potential importance of considering DBH in climate reconstructions *[but these reconstructions are often selecting trees at much bigger dbhs that what are at these sites.]* Traditional dendro methods seek to remove the influence of , but our finding of prevalent - interactions indicate that it should not be ignored. *(Indeed, this is probably one factor contributing to the non-stationarity of climate signals in tree-ring records (Wilmking et al., 2020).)* *( Interactive effects of DBH and climate may suggest significant impact of different sampling strategy on results per individual site. – e.g., stronger drought signal if just large trees are sampled. This is consistent with the dendro tradition of sampling canopy trees for strongest drought signals; however, our results suggest that temperature signals may be stronger in young trees. )* *(height vs exposure/ social status of trees)*

*Recommendations*

Need to record/ preserve DBH. DBH is not always collected when cores are taken, and is not routinely preserved alongside tree-ring data. For example, the International Tree-Ring Data Bank (ITRDB) contains no structure for storing DBH records. DEN is new alternative (Rayback et al., 2020).

Also need to record canopy positions.

Sampling small trees should be important for disentangling whether non-stationarity of climate signals is a size artifact or driven by something else, may also be better for resolving temperature signals.

*Conclusions*

Sets the foundation for considering other, slowly changing environmental drivers.

Framework can be used with other variables.

Scotty temperture responses are probably not physiological, but due to permafrost.

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# Authors’ contributions

KAT, VH, CR, RA, CP conceived the ideas and designed methodology; [most authors] collected the data; VH, BG, EGA, and NP organized and analysed the data; KAT led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

# Data availability

*To enable readers to locate archived data from papers, we require that authors list the database and the respective accession numbers or DOIs for all data from the manuscript that has been made publicly available.*

Code and full results are available via the project repository in GitHub (github.com/EcoClimLab/ForestGEO-climate-sensitivity) and archived in Zenodo (DOI: TBD) . Data for # of the sites are archived in the The DendroEcological Network (DEN) database (Rayback et al., 2020).

# Supplementary files

Appendix S2. Methods for reconstruction of

Appendix S3. Methods for climate data evaluation and correction

Appendix S4. Methods for comparing our approach with traditional methods

Appendix S5. Dealing with rapidly changing climate and tree growth

Table S1. Site Details.

Table S2. Species analyzed, their characteristics, and bark allometries applied.

Table S3. Sampling details for species by site.

Table S4. Allometric equations for bark thickness.

Table S5. Qualtiative comparison of results from this study with previous studies employing conventional methods.

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