Supplementary Information

Contents

Appendix S1. Methods for reconstruction of DBH

For each core, DBH can be reconstructed outside-in (based on recent DBH, subtracting growth recorded in tree rings) or inside-out (summing Δr from the inside out). We generally gave precedence to the outside-in approach. Specifically, when DBH was taken at the time of coring,
At some of our sites where DBH was not taken at the time of coring (*SCBI*,), DBH measurements taken before or slightly after the time of coring could be used. (see issue #19 in ForestGEO_dendro) If before, ... If after... For all outside-in reconstructions, if a negative DBH was predicted...

When there were more than one cores for a tree, the DBH reconstructions from each core were averaged to produce a single estimate of the tree's DBH through time. When the start or end dates of the records from the cores differed, we extrapolated growth of the shorter core to match the years covered by the longer core. Specifically, to fill in years at the more recent end, we assumed that the average growth rate of the ten years prior to the missing records applied to the missing years. To fill in years at the beginning of the tree's lifespan, we likewise assumed that the ten years adjacent to the missing record applied to the missing years; however, if this yielded a negative DBH estimate for the earliest year in the reconstruction, we divided the existing minimum DBH by number of years missing and applied that value to each year. We note that these reconstructed growth records were used only for the reconstruction of DBH and were not included as response variables in any of our analyses.

In either case we need bark thickness–ideally allometries describing the relationship between DBH and bark thickness (Table S4). This is especially critical for thick-barked species When bark thickness data were available, we generated allometries ... lognormal model with intercept forced to zero: lm(bark_depth.mm ~ -1 + log(dbh_no_bark.cm+1):bark_species, data = bark) (issue #8 in ForestGEO_dendro)

Appendix S2. Methods for comparing climwin results with traditional methods

(**ISSUE #35 in ForestGEO-climate-sensitivity

Appendix S3. Dealing with rapidly changing climate and tree growth

ISSUE #25 in ForestGEO-climate-sensitivity

Our analysis included two sites where climate change has had pronounced effects on tree growth: Scotty Creek, NW Territories, Canada (SC) and Little Tesuque, New Mexico, USA (LT). At SC, [temperatures have increased by X ° over X years]…, resulting in negative growth trends in basal area index (BAI) starting around 1950 and significant growth declines since 1970 in 56% of trees [@sniderhan_growth_2016].

Table S1. Site Details

site code	site name	latitude	longitude	cores within ForestGEO plot?	canopy positions	tree statuses	date range	dormant season	months in climwin
BCI	Barro Colorado Island	9.15430	-79.8461	no	canopy	live, dead	1931-2014	Nov-Apr	pOct-cDec
HKK	Huai Kha Khaeng	15.63240	99.2170	no	all	live	1903-2011		pOct-cDec
LT	Little Tesuque	35.73838	-105.8382	n.a.	all	live	1903-2018		pMay-cAug
CB	Utah Forest Dynamics Plot	37.66150	-112.8525				1903-2007		pMay-cAug
SCBI	Smithsonian Conservation Biology Institute	38.89350	-78.1454	yes	all	live, dead	1903-2017	Oct-Apr	pMay-cAug
LDW	Lilly Dickey Woods	39.23590	-86.2181		canopy	live, dead	1903-2019		pMay-cAug
HF	Harvard Forest	42.53880	-72.1755	yes	all	live, dead	1903-2014		pMay-cAug
NB	Niobrara/Hansley	42.78000	-100.0210						pMay-cAug
ZOF	Zofin Forest Dynamics Plot	48.66380	14.7073	some	all		1903-2013		pMay-cAug
SC	Scotty Creek	61.30000	-121.3000	no	all	live, dead	1903-2013		pMay-cAug

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

(**ISSUE #72 in ForestGEO-climate-sensitivity

species code	family	latin name	site(s) sampled	leaf type	leaf phenology	light requirements	bark allometry*
$species_codeinsitespecies.csv$	family in sitespecies.csv	$latin_name$ in sitespecies.csv	site codes	$leaf_type$ in sitespecies.csv	$leaf_phenology$ in sitespecies.csv	$light_requirements$ in sitespecies.csv	"$bark_species$ in $bark_site$"

*Bark allometry field indicates the species and site sampled to construct the bark allometry. When neither raw data nor an allometric equation for the study species was available, we selected the most appropriate equation that could be located for similar species. Equations are given in Table S4.

Table S3. Sampling details for species by site

(ISSUE #73 in ForestGEO-climate-sensitivity)

Table S4. Allometric equations for bark thickness

species	**equation**	**n**	**DBH.range.cm**	**site**	**source**
Acer rubrum	$bark.mm = 0.619 * log(dbh.cm + 1)$	10	8.2-39.6	SCBI	Anderson-Teixeira et al. (2015)
Carya cordiformis	$bark.mm = 0.793 * log(dbh.cm + 1)$	9	5.9-68.2	SCBI	Anderson-Teixeira et al. (2015)
Carya ovalis	$bark.mm = 1.531 * log(dbh.cm + 1)$	8	6.4-63.1	SCBI	Anderson-Teixeira et al. (2015)
Carya ovata	$bark.mm = 1.035 * log(dbh.cm + 1)$	8	19.1-78	SCBI	Anderson-Teixeira et al. (2015)
Carya tomentosa	$bark.mm = 1.105 * log(dbh.cm + 1)$	8	5-57.3	SCBI	Anderson-Teixeira et al. (2015)
Fraxinus americana	$bark.mm = 2.223 * log(dbh.cm + 1)$	9	6.1-94.2	SCBI	Anderson-Teixeira et al. (2015)
Jacaranada copaia	$bark.mm = 2.993 * log(dbh.cm + 1)$	5	45.6-75	Panama	Raquel Alfaro-Sanchez (unpublished data)
Juglans nigra	$bark.mm = 2.107 * log(dbh.cm + 1)$	9	13.6-85.4	SCBI	Anderson-Teixeira et al. (2015)
Liriodendron tulipifera	$bark.mm = 1.637 * log(dbh.cm + 1)$	9	27.5-136.5	SCBI	Anderson-Teixeira et al. (2015)
Picea mariana	$bark.mm = 3.726 * log(dbh.cm + 1)$	12	6.9-7.9	Scotty Creek	Anastasia Sniderhan and Jennifer Baltzer (unpublished data)
Pinus flexilis	$bark.mm = (1.299 * \sqrt{(dbh.cm)^{0.609}})^2$	29	10-130	California (3 montane sites)	Zeibig-Kichas et al. (2016)
Pinus ponderosa	$bark.mm = (1.298 * \sqrt{(dbh.cm)^{0.802}})^2$	81	5-160	California (4 montane sites)	Zeibig-Kichas et al. (2016)
Pinus strobus	$bark.mm = 1.568 * log(dbh.cm + 1)$	1	28.4-28.4	Illinois	Miles and Smith (2009)
Pseudotsuga menziesii	$bark.mm = (0.785 * \sqrt{(dbh.cm)})^2$	30	10-200	California (3 montane sites)	Zeibig-Kichas et al. (2016)
Quercus alba	$bark.mm = 1.828 * log(dbh.cm + 1)$	10	9.3-101.8	SCBI	Anderson-Teixeira et al. (2015)
Quercus montana	$bark.mm = 2.083 * log(dbh.cm + 1)$	8	5.8-99.1	SCBI	Anderson-Teixeira et al. (2015)
Quercus rubra	$bark.mm = 0.98 * log(dbh.cm + 1)$	10	24.1-143.2	SCBI	Anderson-Teixeira et al. (2015)
Quercus velutina	$bark.mm = 1.394 * log(dbh.cm + 1)$	8	16.2-110.7	SCBI	Anderson-Teixeira et al. (2015)
Tetragastris panamensis	$bark.mm = 1.672 * log(dbh.cm + 1)$	4	22.7-48.8	Panama	Raquel Alfaro-Sanchez (unpublished data)
Trichilia tuberculata	$bark.mm = 1.367 * log(dbh.cm + 1)$	12	21-40.5	Panama	Raquel Alfaro-Sanchez (unpublished data), Pete Kerby-Miller and Helene Muller-Landau (unpublished data)

Table S5. Frequency of DBH-climate interactions across all sites and growth metrics

Figure S1. Comparison of our approach with traditional methods of identifying climate signals

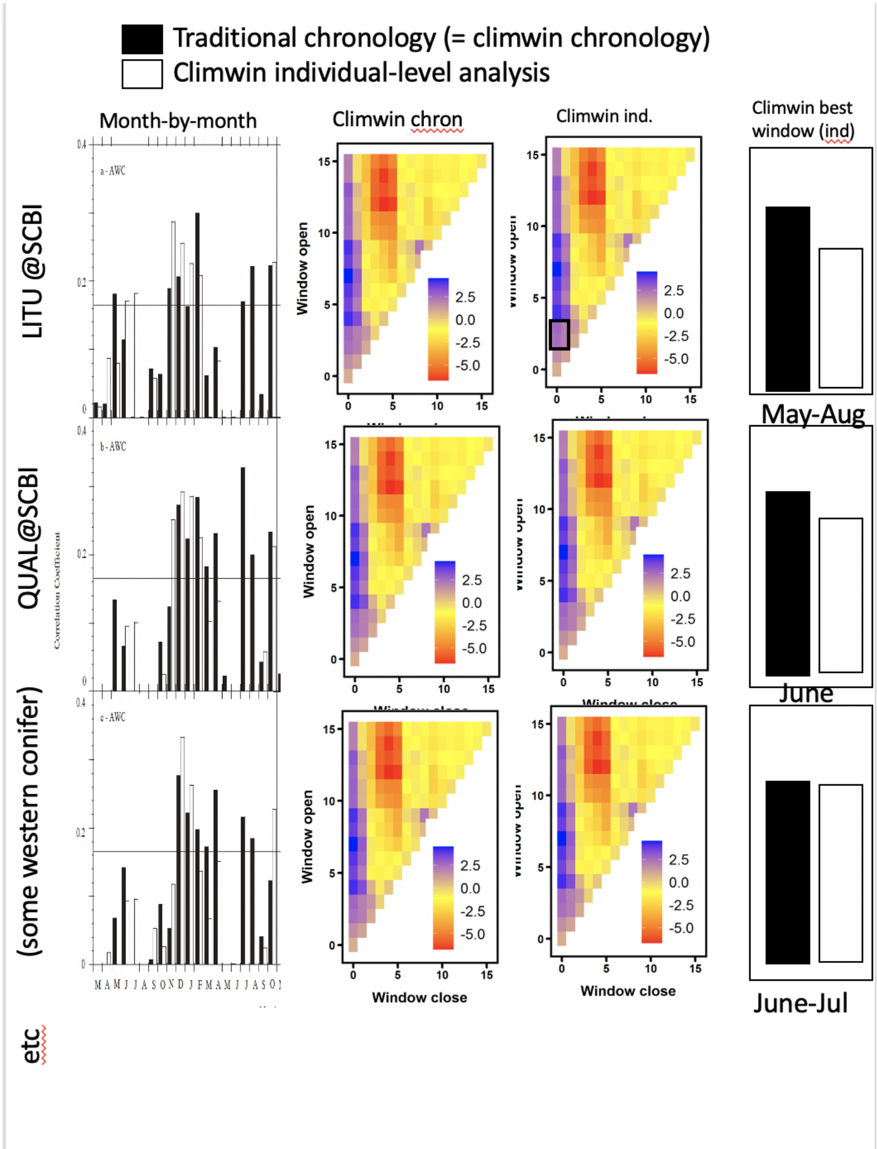

Figure S1 | (Comparison of traditional approaches with ours). (THIS FIGURE IS JUST A MOCK-UP TO SHOW VALENTINE WHAT I HAVE IN MIND.)

Figure S2. Comparison of climwin output across growth metrics for the temperature variable group at Little Tesuque (New Mexico, USA)

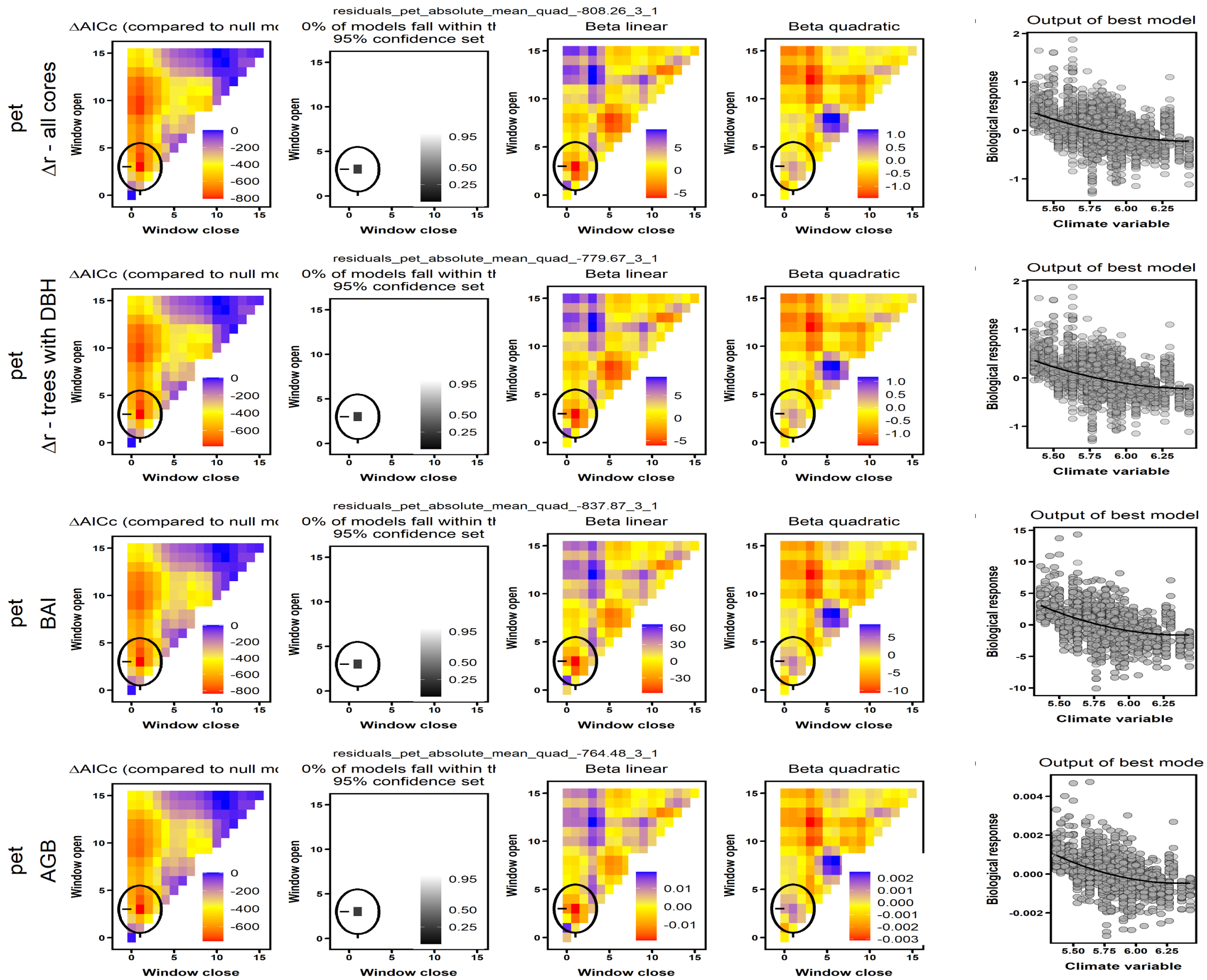

Figure S2 | Comparison of climwin output across growth metrics for the temperature variable group at Little Tesuque (New Mexico, USA). Here, *climwin* identified potential evapotranspiration (PET) as the strongest climate variable across all three metrics of growth (Δr, BAI, ΔAGB) and regardless of whether all cores were included in the analysis, or only those for which DBH could be reconstructed (Δr-trees with DBH, BAI, ΔAGB).)

Figure S3. Comparison of climwin output across growth metrics for the precipitation variable group at Little Tesuque (New Mexico, USA)

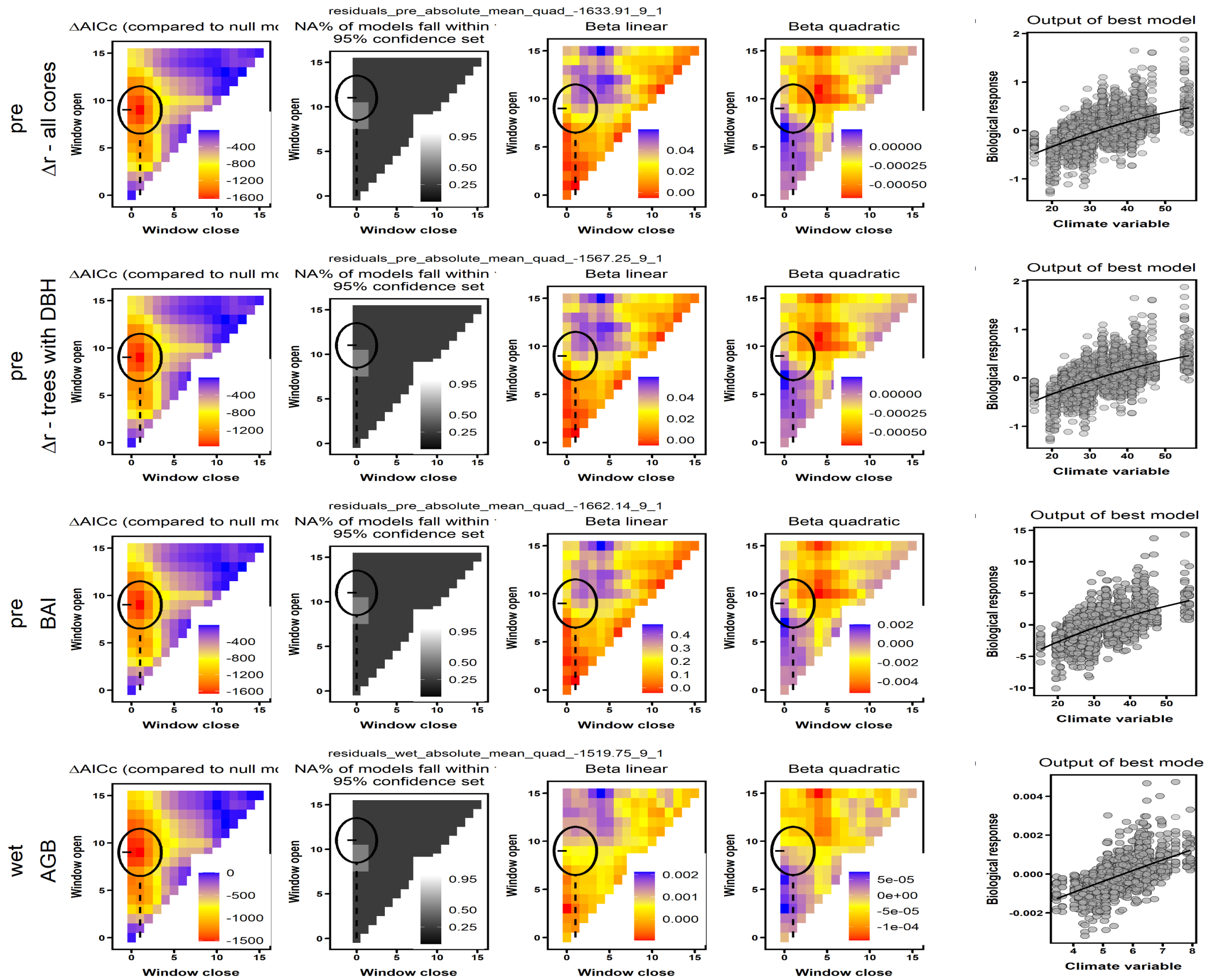

Figure S3 | Comparison of climwin output across growth metrics for the precipitation variable group at Little Tesuque (New Mexico, USA). Here, *climwin* identified precipitation (PRE) as the strongest climate variable for Δr and BAI, but precipitation day frequency (WET) as the strongest climate variable for ΔAGB.

Figure S4. Comparison of climwin output across growth metrics for the precipitation variable group at Harvard Forest (Massachusetts, USA)

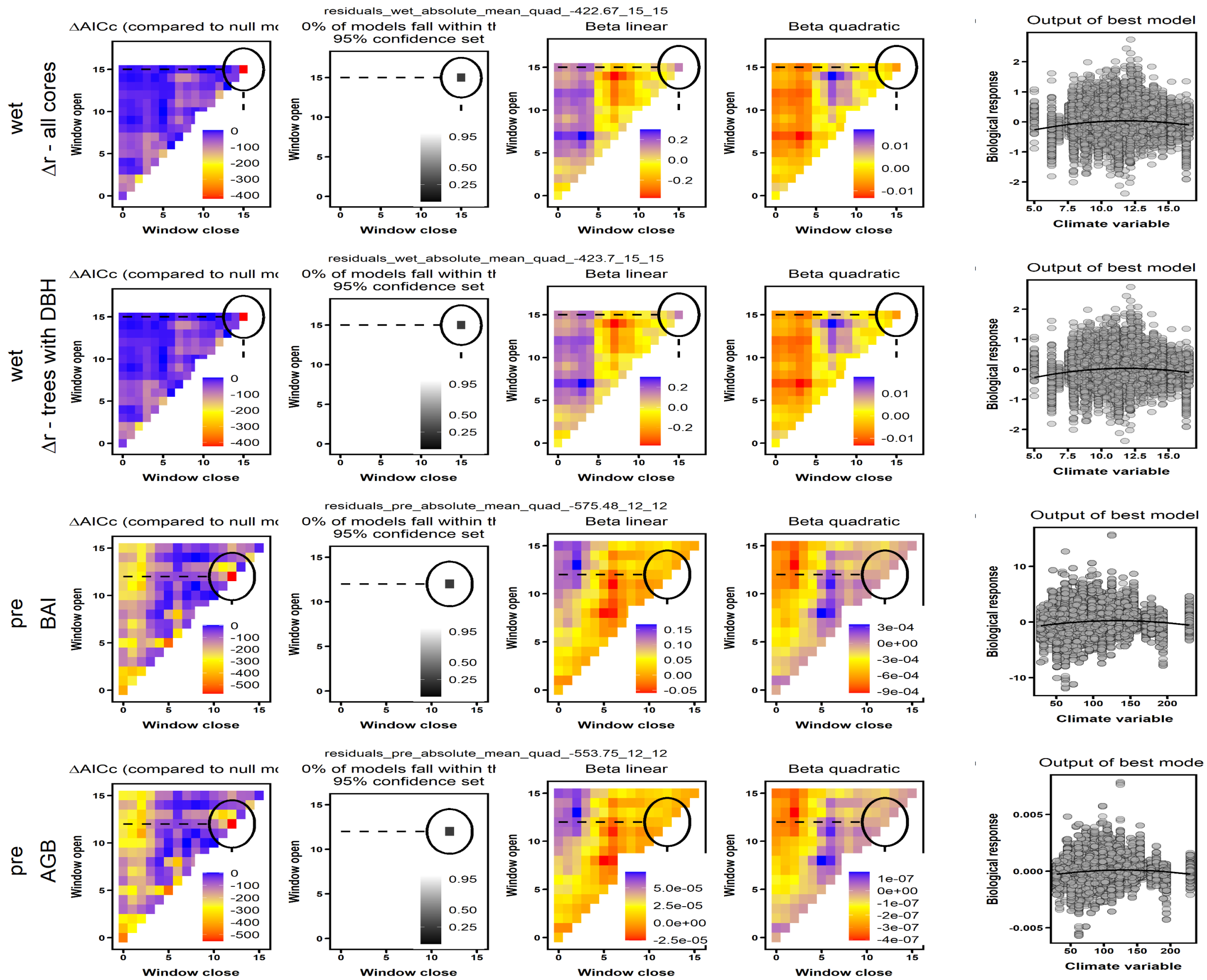

Figure S4 | Comparison of climwin output across growth metrics for the precipitation variable group at Harvard Forest (Massachusetts, USA). Here, *climwin* identified precipitation frequency (WET) as the strongest climate variable for Δr, but precipitation amount (PRE) as the strongest climate variable for BAI and ΔAGB. The optimal time window (circled) also differed across growth metrics.

Figure S5. Best GLS models for Barro Colorado Island (Panama)

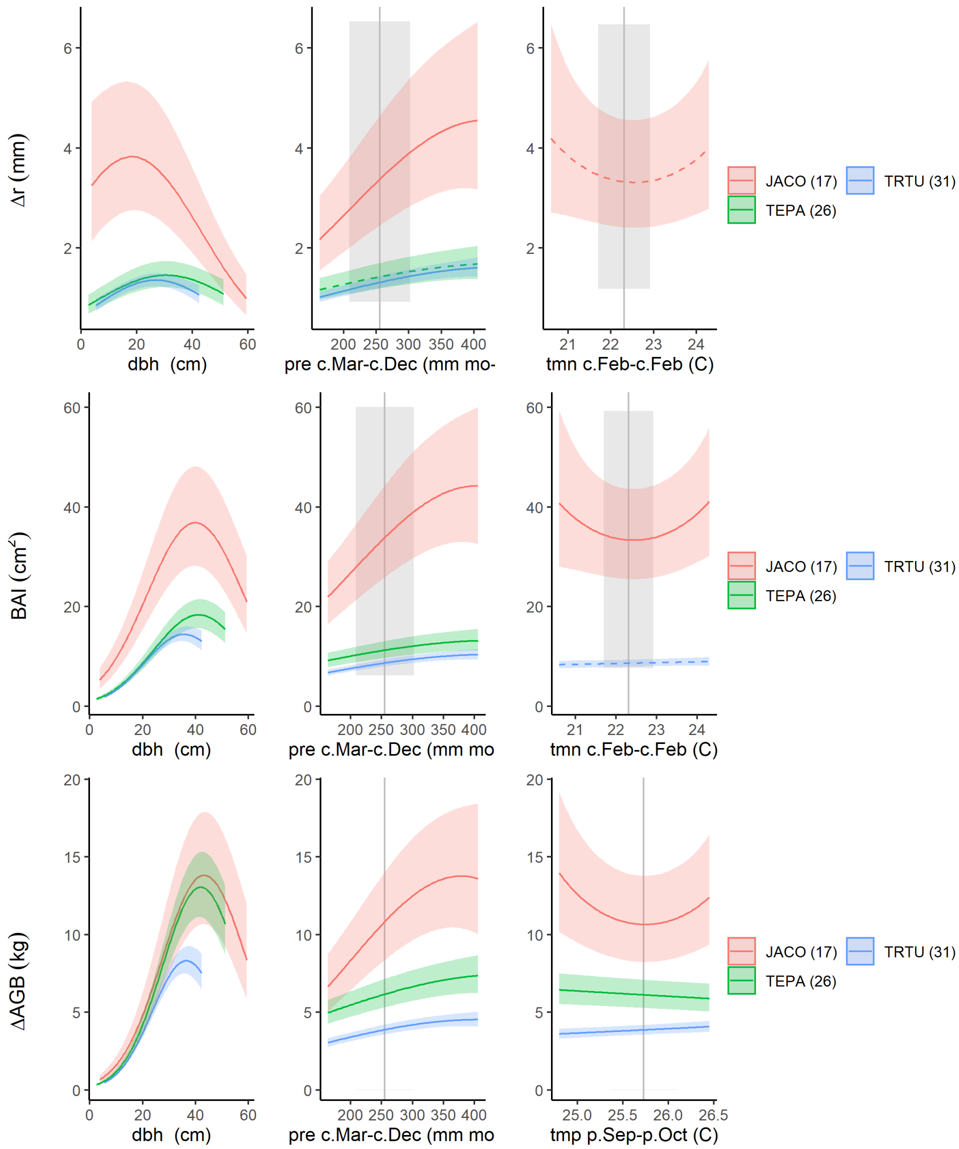

Figure S5 | Best GLS models for Barro Colorado Island (Panama) for all three growth metrics: Δr, BAI, and ΔAGB. Precipitation and temperature group variables are as selected by *climwin*. For each species, relationships are plotted if included in top model, with dashed lines indicating terms that do not significantly improve the model (relative to a model without). Vertical grey lines indicate the long-term mean for the climate variable, shading indicates 1 SD.

Figure S6. Best GLS models for Huai Kha Khaeng (Thailand)

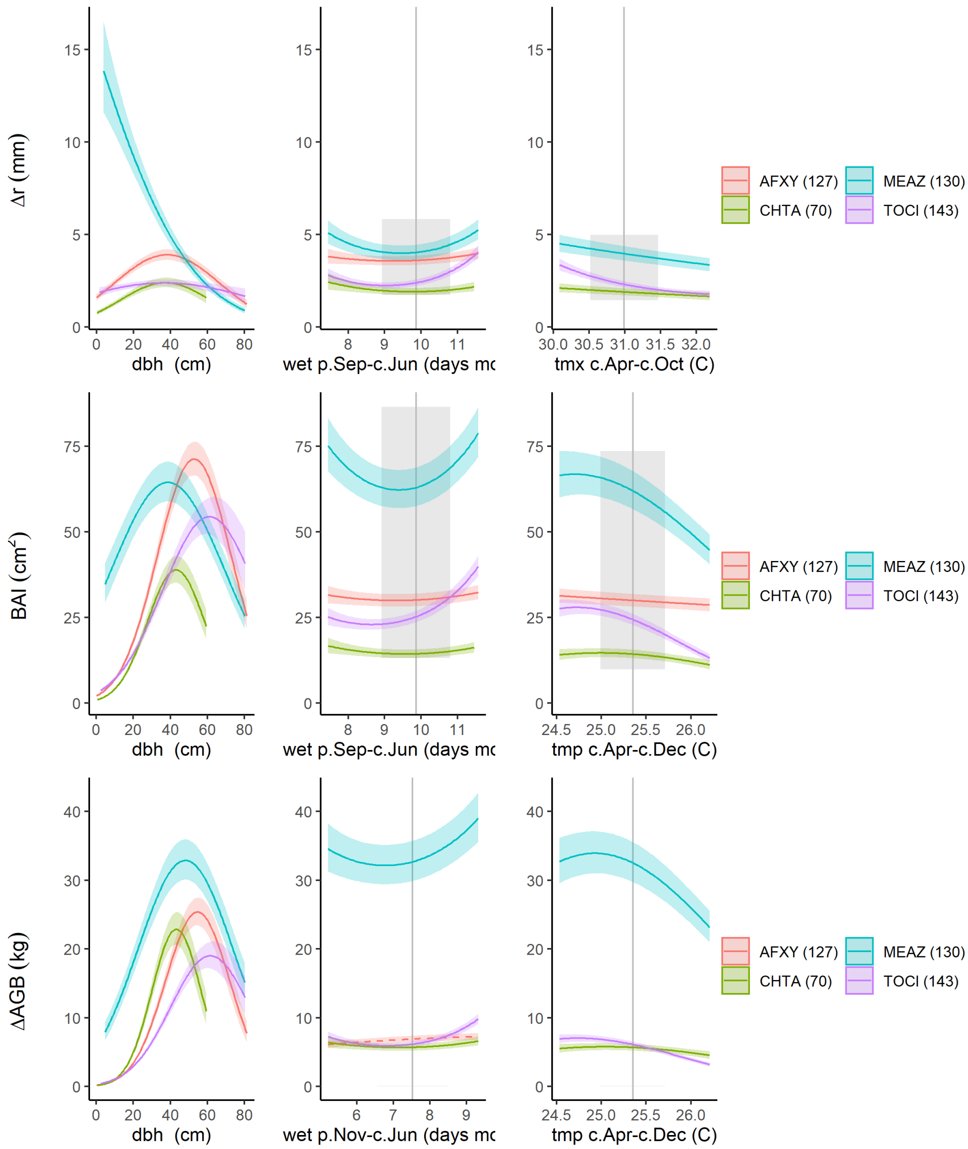

Figure S6 | Best GLS models for Huai Kha Khaeng (Thailand) for all three growth metrics: Δr, BAI, and ΔAGB. Precipitation and temperature group variables are as selected by *climwin*. For each species, relationships are plotted if included in top model, with dashed lines indicating terms that do not significantly improve the model (relative to a model without). Vertical grey lines indicate the long-term mean for the climate variable, shading indicates 1 SD.

Figure S7. Best GLS models for Little Tesuque (New Mexico, USA)

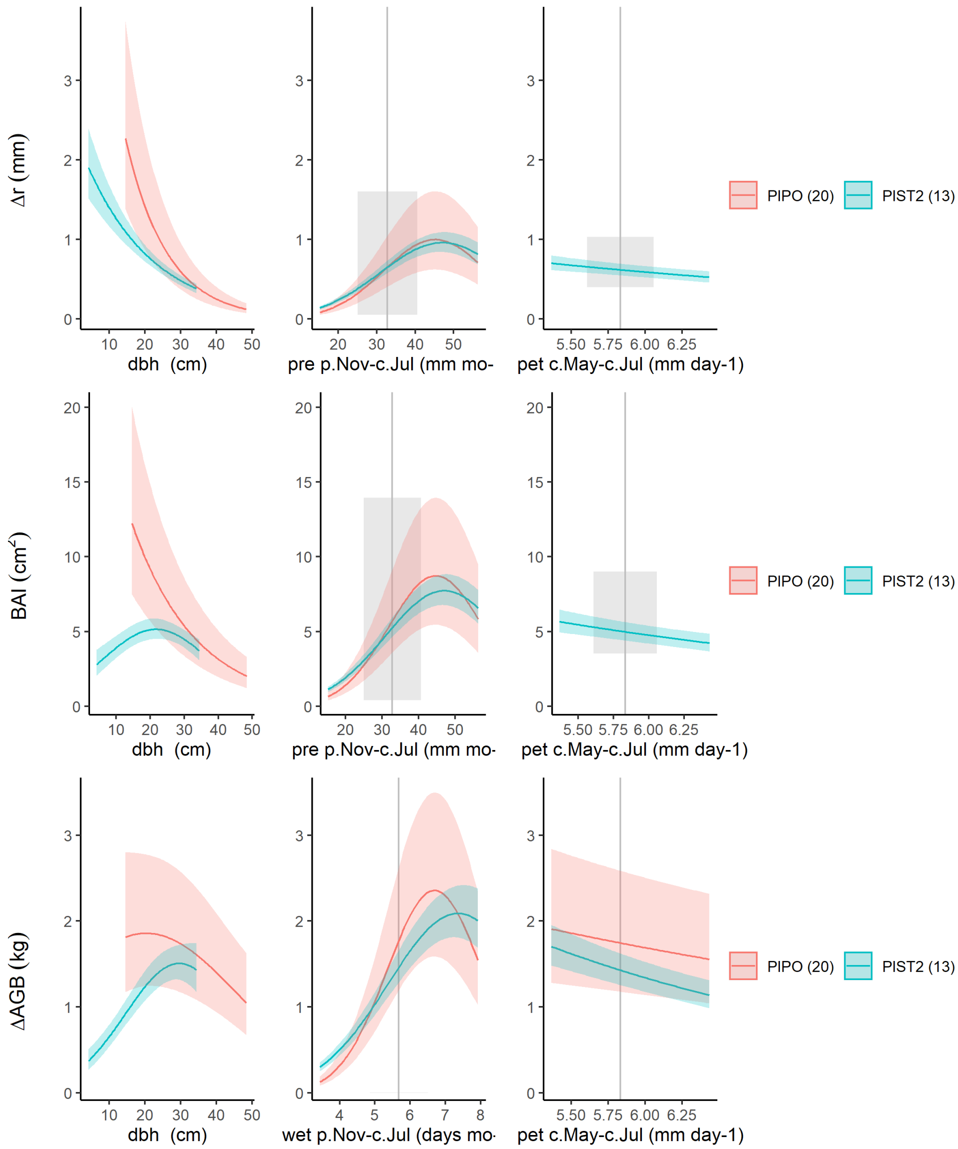

Figure S7 | Best GLS models for Little Tesuque (New Mexico, USA) for all three growth metrics: Δr, BAI, and ΔAGB. Precipitation and temperature group variables are as selected by *climwin*. For each species, relationships are plotted if included in top model, with dashed lines indicating terms that do not significantly improve the model (relative to a model without). Vertical grey lines indicate the long-term mean for the climate variable, shading indicates 1 SD.

Figure S8. Best GLS models for Cedar Breaks (Utah, USA)

[**Figure S8 | Best GLS models for Cedar Breaks (Utah, USA) for all three growth metrics: Δr, BAI, and ΔAGB.** Precipitation and temperature group variables are as selected by *climwin*. For each species, relationships are plotted if included in top model, with dashed lines indicating terms that do not significantly improve the model (relative to a model without). Vertical grey lines indicate the long-term mean for the climate variable, shading indicates 1 SD.]

Figure S9. Best GLS models for SCBI (Virginia, USA)

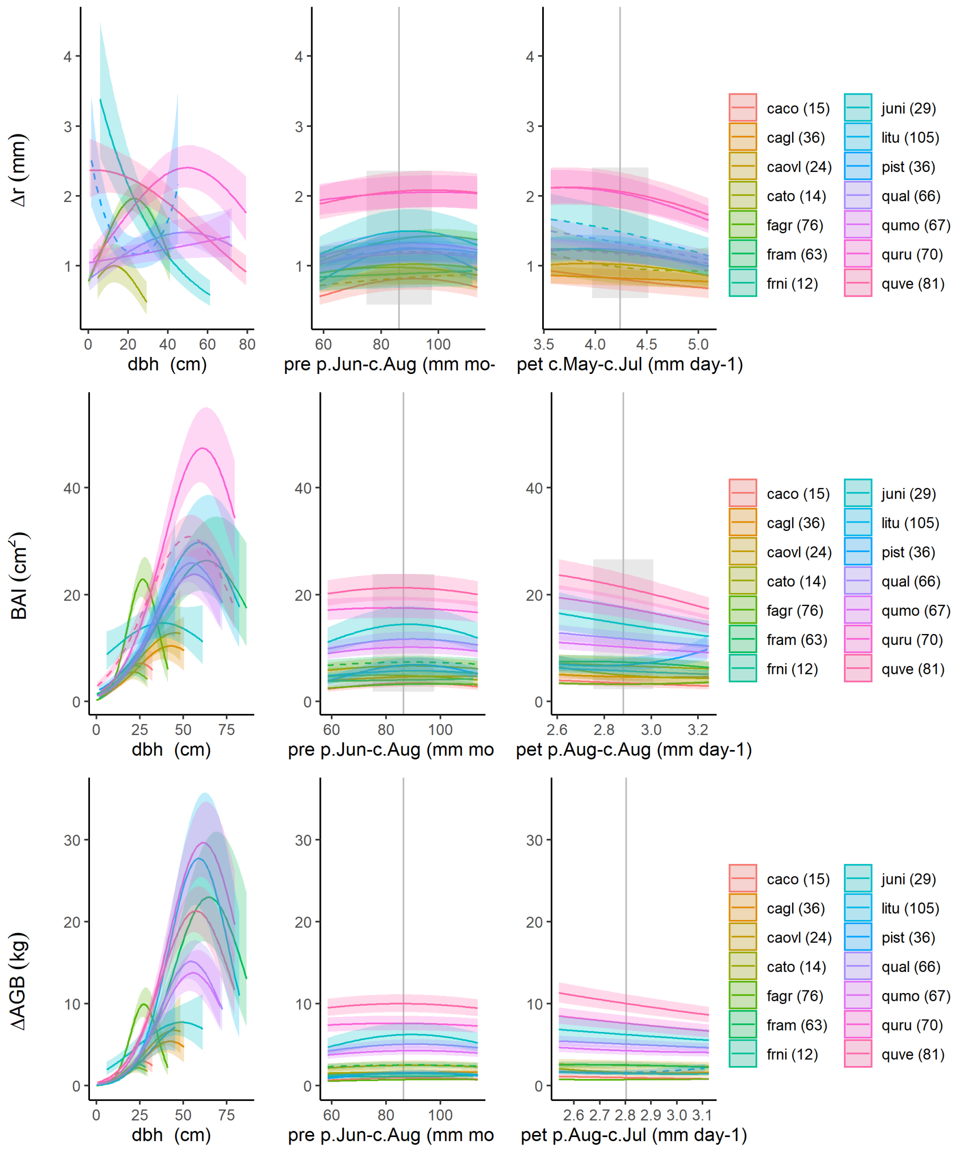

Figure S9 | Best GLS models for SCBI (Virginia, USA) for all three growth metrics: Δr, BAI, and ΔAGB. Precipitation and temperature group variables are as selected by *climwin*. For each species, relationships are plotted if included in top model, with dashed lines indicating terms that do not significantly improve the model (relative to a model without). Vertical grey lines indicate the long-term mean for the climate variable, shading indicates 1 SD.

Figure S10. Best GLS models for Lilly Dickey Woods (Indiana, USA)

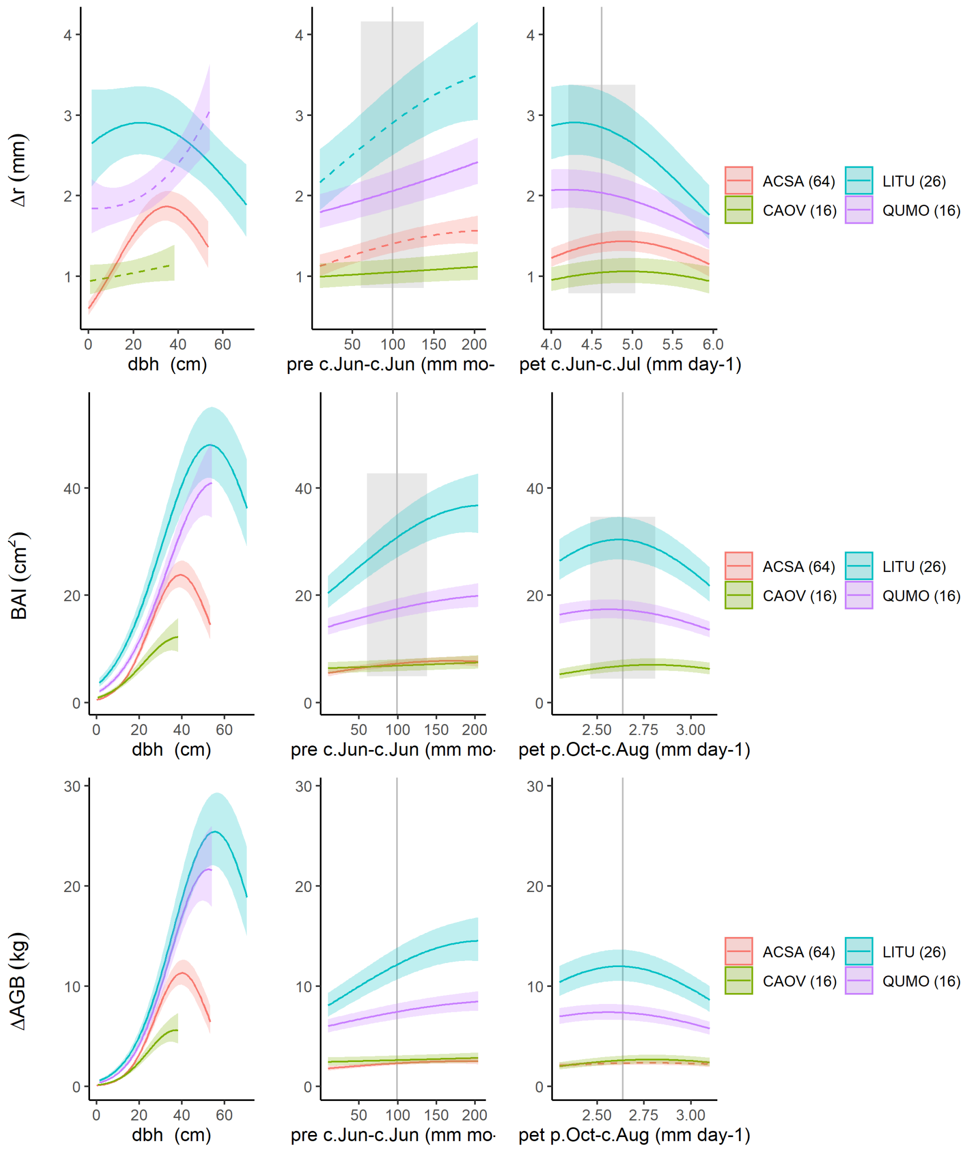

Figure S10 | Best GLS models for Lilly Dickey Woods (Indiana, USA) for all three growth metrics: Δr, BAI, and ΔAGB. Precipitation and temperature group variables are as selected by *climwin*. For each species, relationships are plotted if included in top model, with dashed lines indicating terms that do not significantly improve the model (relative to a model without). Vertical grey lines indicate the long-term mean for the climate variable, shading indicates 1 SD.

Figure S11. Best GLS models for Harvard Forest (Massachusetts, USA)

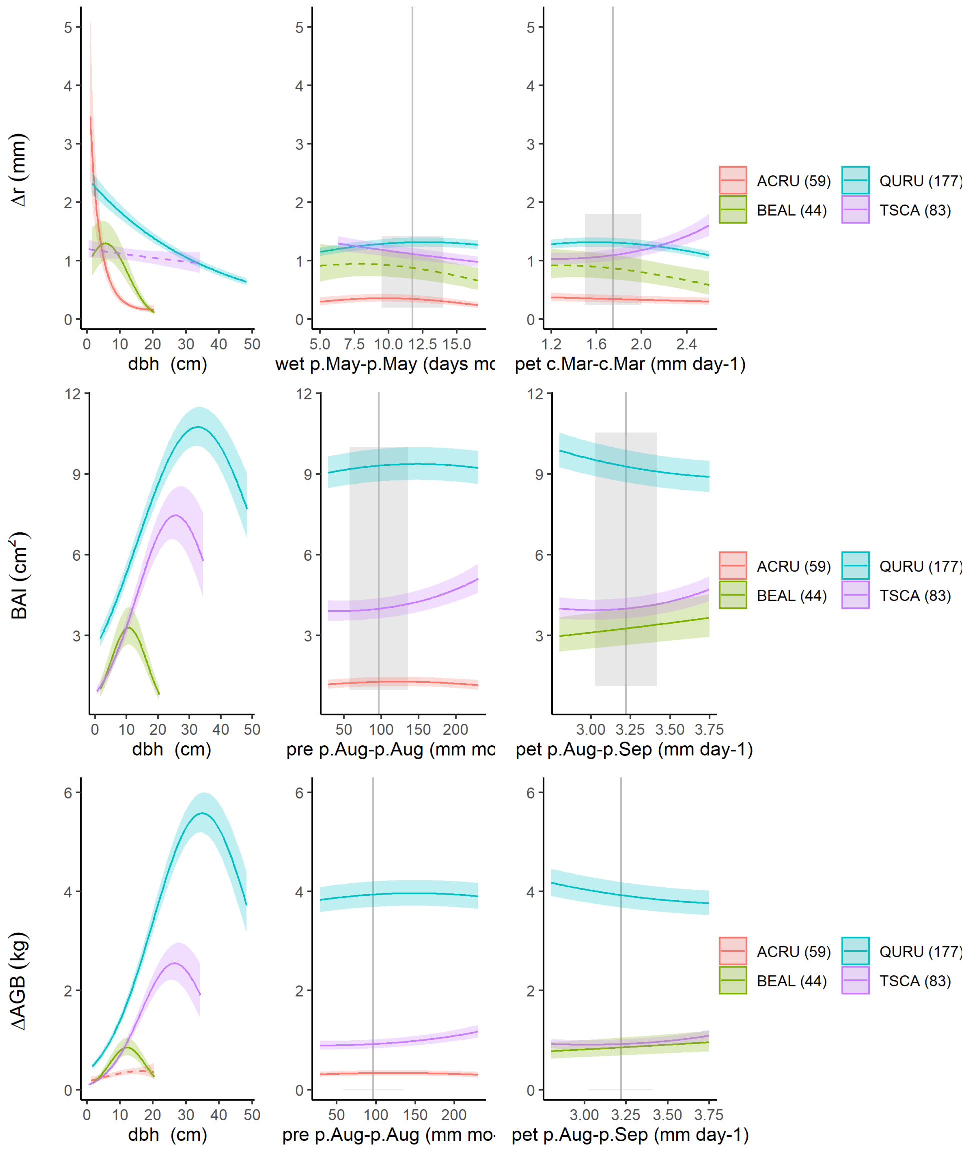

Figure S11 | Best GLS models for Harvard Forest (Massachusetts, USA) for all three growth metrics: Δr, BAI, and ΔAGB. Precipitation and temperature group variables are as selected by *climwin*. For each species, relationships are plotted if included in top model, with dashed lines indicating terms that do not significantly improve the model (relative to a model without). Vertical grey lines indicate the long-term mean for the climate variable, shading indicates 1 SD.

Figure S12. Best GLS models for Niobrara/ Hansley (Nebraska, USA)

Figure S13. Best GLS models for Zofin (Czech Republic)

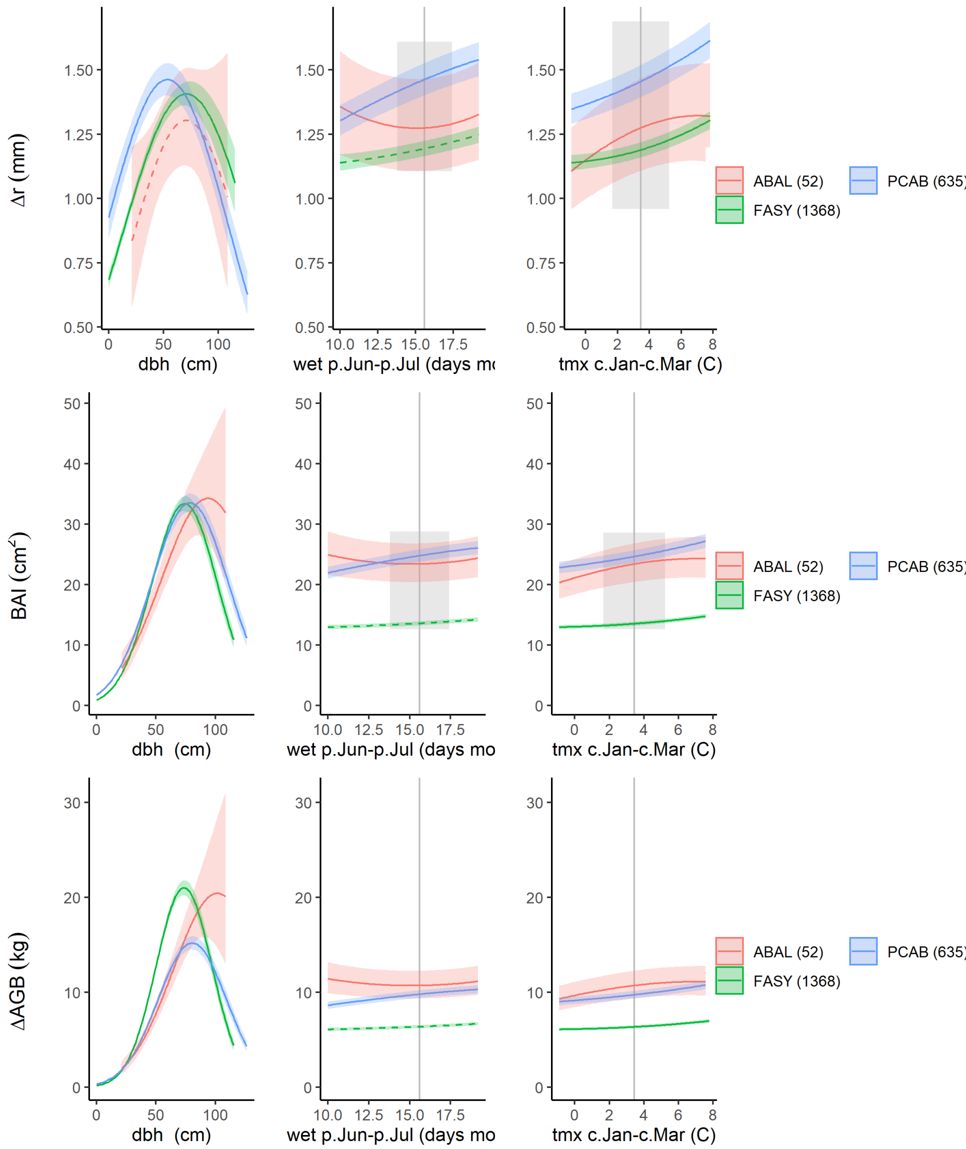

Figure S13 | Best GLS models for Zofin (Czech Republic) for all three growth metrics: Δr, BAI, and ΔAGB. Precipitation and temperature group variables are as selected by *climwin*. For each species, relationships are plotted if included in top model, with dashed lines indicating terms that do not significantly improve the model (relative to a model without). Vertical grey lines indicate the long-term mean for the climate variable, shading indicates 1 SD.

Figure S14. Best GLS models for Scotty Creek (NW Territories, Canada)

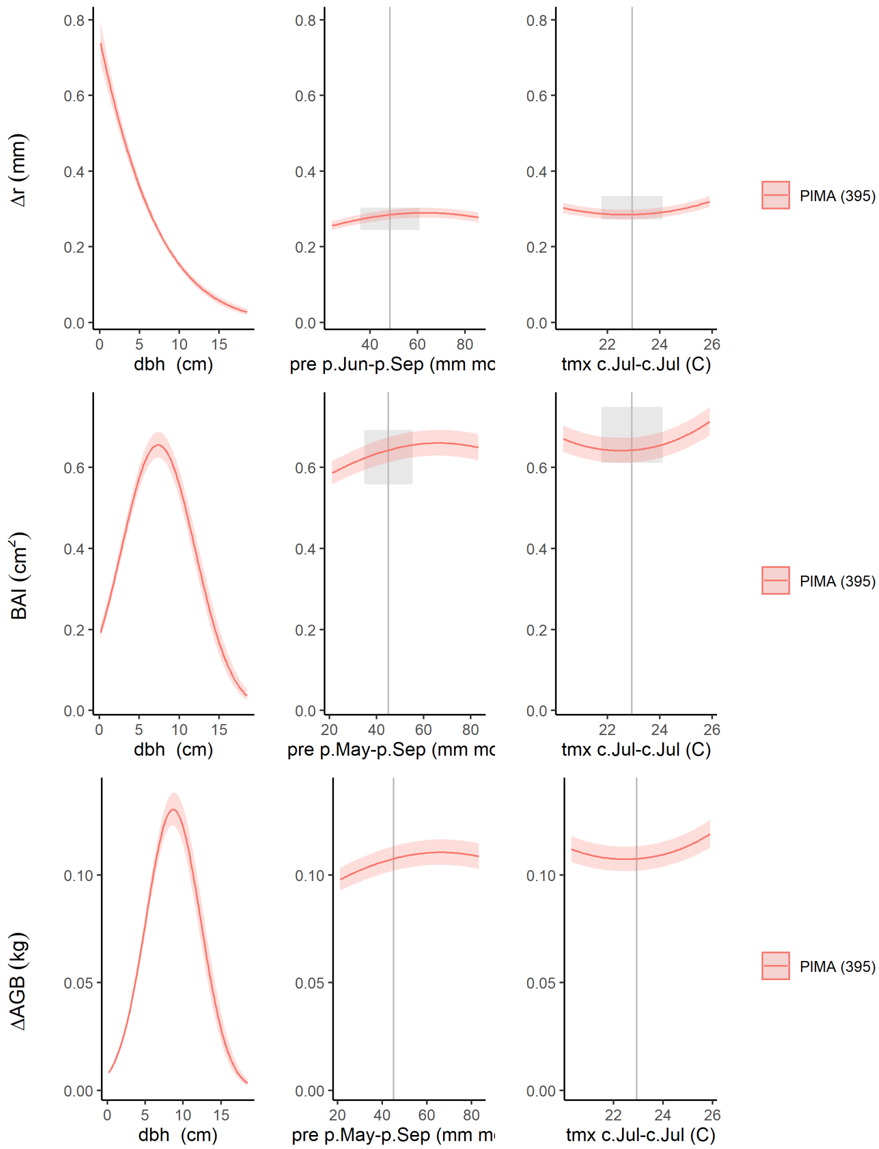

Figure S14 | Best GLS models for Scotty Creek (NW Territories, Canada) for all three growth metrics: Δr, BAI, and ΔAGB. Precipitation and temperature group variables are as selected by *climwin*. For each species, relationships are plotted if included in top model, with dashed lines indicating terms that do not significantly improve the model (relative to a model without). Vertical grey lines indicate the long-term mean for the climate variable, shading indicates 1 SD.