



Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Influence of climate and competition on growth sensitivity and trends of *Fagus sylvatica* in the largest primeval beech forest of Europe

(Uholka-Shyrokyi Luh massif in SW-Ukraine)

Master's thesis at the Institute for Terrestrial Ecosystems (ITES)

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Summary

European beech (*Fagus sylvatica* L.) is the most abundant broadleaf tree species in Central Europe. Understanding the processes that drive growth of *F. sylvatica* is critical to predict future dynamics in natural- and primeval- beech forests under climate change. In this study we analyzed the effect of climate and competition on radial growth of beech in the Uholka-Shyrokyi Luh massif in southwestern Ukraine, the largest primeval beech forest reserve of the world. Yearly radial growth data from 249 increment cores was combined with climatic data extracted from the 1-km resolution CHELSAcruts climate dataset to assess the sensitivity of beech trees to climate. To represent the combined effect of precipitation and temperature we computed the climatic water balance for each month and each plot. We then calculated bootstrapped correlation coefficients for each individual tree-ring chronology and all climatic variables (maximum temperature, minimum temperature, precipitation, and climatic water balance) in order to select the most influential climatic parameters subsequent mixed-effects modelling. To test for an effect of competition on growth and climate sensitivity we calculated a spatially-explicit competition index based on the data from the terrestrial inventory. Assuming little to no changes in competitive status over the last two decades, we fitted an exponential decay function to mean BAI and competition for the period of 1989-2009. We defined the y-intercept as the growth potential (expected growth under no competition) and calculated the competition index corresponding to a 50% decrease in growth. We then created two subsamples from the data grouping trees with competition values above or below the calculated threshold respectively. Finally, we used linear mixed-effects models to model basal area increment as a function of tree size and climate. The same model was fitted to the two competition subsamples to evaluate potential differences in climate sensitivity.

Our results show that growth of beech was only slightly sensitive to climate. Tree size was the most influential factor explaining a substantial part of variance in basal area increment. Among the modelled climatic variables, winter temperature had the strongest positive effect on growth. Moreover, trees benefitted from elevated summer temperatures and reduced summer climatic water balance, suggesting that drought is not an important factor limiting the growth of beech in the study area. These results indicate that projected climate change is likely to have a beneficial effect on the growth of beech in the near future. We observed a significant interaction between tree size and the effect of summer climatic water balance on growth, suggesting that larger trees benefit more from high moisture availability than smaller trees. Trees experiencing high levels of competition were also generally smaller and grew less vigorously than trees experiencing little competition. For trees experiencing high levels of competition, growth was less significantly correlated to climate than across the sample of low competition trees. However, we found no proof of growth reactions to climate varying systematically with the level of competition.

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1 Introduction

Terms such as natural-, virgin-, or primeval-forest are frequently used to describe forest that developed with minimal anthropogenic influence (A. Nagel *et al.*, 2013). Even though natural forests are composed of the same species mixture as primeval- or virgin- forests, age structure or abundance of specific species tend to differ from observations in primeval forests (Parviainen, 2005). Because these forests have developed in the absence of human influence, they provide valuable insight into natural processes such as forest dynamics, tree demographics, species composition, and growth under natural competition (Foster *et al.*, 1996; Brändli & Dowhanytsch, 2003; Commarmot *et al.*, 2009). Natural forests are characterized by the presence of all development stages and high structural heterogeneity. In contrast to managed forests where trees in a stand usually belong to the same age-cohort, natural forests contain trees of all ages and sizes that may appear throughout the entirety of the forest, leading to a small-scale mosaic of different development stages shaped by natural disturbances (Korpel, 1995). Due to the absence of management, very large trees are more abundant and high amounts of deadwood are observed more frequently than in managed forests (Commarmot *et al.*, 2005; A. Nagel *et al.*, 2013).

Historically, the forests of Europe have been under strong pressure by human exploitation and have provided many of the essential goods and services for human development. This strong dependence on forest products in the past led to widespread overexploitation of forests throughout Europe. It was not until the 18th century that the notion of “sustainable forest management” emerged, mostly as a measure to achieve long-term sustainable timber production. Coniferous species have long been the focus of this effort. More recently, management practices have evolved and now aim to transform conifer monocultures into more structured forests and increase natural regeneration. In particular, the promotion of regeneration of European beech (*Fagus sylvatica* L.) is widely supported by forest practitioners. Beech is the most abundant and widespread broadleaf tree species in Central Europe (Fig. 1). Due to its strong relative competitiveness, it dominates extensive forested areas throughout Europe within its ecological range (Peters, 1997). Beech is characterized by exceptionally high shade tolerance during early life and tends to form monodominant stands with a dense closed canopy (Helliwell, 2012). Because of the high tolerance for shade of beech seedlings and saplings, regeneration can take place under an almost-closed canopy. The pre-established regeneration can survive in deep shade for a long time and can react swiftly to changing conditions such as additional light influx, caused by new openings in the canopy. However, it frequently develops a shallow root system that makes it susceptible to drought (Peterken & Mountford, 1996; Köcher *et al.*, 2009). Consequently, beech suffers much higher losses than most other species in years with strong summer drought (Packham *et al.*, 2012). Because of the high abundance and importance of beech for central European silviculture, concerns have been raised as to, whether beech will maintain dominance and its vigorous growth within its current range. As climate projections generally predict increasing temperatures, decreasing precipitation, and resultant increases in drought frequency and severity, beech may lose its competitive advantage and be replaced by more drought tolerant species. It therefore seems likely that future changes in climate will have a strong effect on beech, particularly at the southern extremes of its range (Peñuelas *et al.*, 2008). However, little is known about the reaction of beech to climate change in forests at the eastern edge of its range where growth may be limited by low summer temperatures rather than drought.

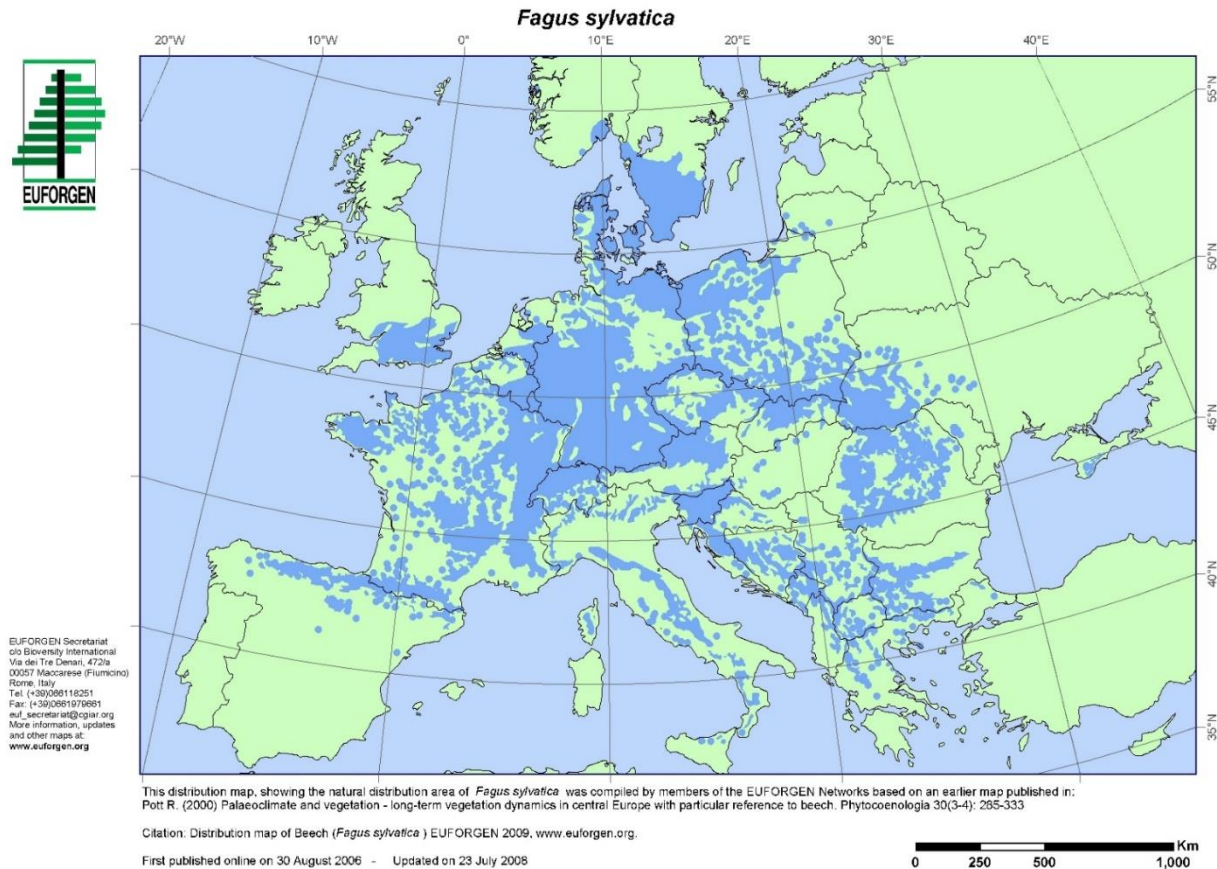


Fig. 1 Distribution map of *F. sylvatica*. EUFORGEN 2009, www.euforgen.org

Inter-tree competition is an important driver of forest dynamics (Kunstler *et al.*, 2011). Where growth is limited by water and/or light, trees compete for these resources. Thus, trees of different sizes and competition status may differ in their reaction to climate (Sanchez-Salguero *et al.*, 2015). Forest structure, climate and site conditions influence the growth of trees in a way such that growth of neighboring trees can be highly variable. This effect is especially pronounced in natural forests where trees of different ages and sizes compete for light and resources. Understanding the relative contribution of competition and climate to growth is crucial to accurately estimate future forest dynamics under climate change (Lindner *et al.*, 2010).

To better understand the dynamics and processes influencing growth of European beech in natural beech forests, we combined growth data from an extensive tree-ring dataset with forest inventory data covering the entire Uholka-Shyrokyi Luh primary forest reserve. Taking advantage of this unique dataset we aim at providing new insights into the growth and sensitivity to climate of European beech in primeval forests in southwestern Ukraine. Specifically, we addressed the following research questions:

- 1) What are the long-term growth trends of *F. sylvatica* in the Uholka-Shyrokyi Luh primeval forest reserve??
- 2) How do tree size, competition, and climate influence radial growth of *F. sylvatica*?
- 3) Is there a difference in climate sensitivity between trees experiencing different levels of competition?

2 Study area

One of the largest protected areas in Eastern Europe is the Carpathian Biosphere Reserve (CBR) situated in the Eastern Carpathians (Fig. 2). Originally established in 1968 as a nature reserve, it became part of the UNESCO World Network of Biosphere Reserves in 1992. The CBR is made up of 8 separate massifs covering a total area of 53,630 hectares. Over 80% (44,100 ha) of the CBR is covered with forests. The CBR covers many characteristic communities of the southern slopes of the Carpathians: foothill oak forests (180 - 450 m.a.s.l.) and mountain beech and mixed forests (450 – 1,000 m.a.s.l.) dominate most of the lowlands, whereas the higher altitudes are covered with mixed beech and spruce forests (1,000 – 1,450 m.a.s.l.), subalpine crooked woodland (1,450 – 1,800 m.a.s.l.) and alpine meadows (1,800 – 2,061 m.a.s.l.) (UNESCO, 2011).



Fig. 2 Location of the Uholka-Shyrokyi Luh protected area. Own adaptation based on Brändli and Dowhanytsch (2003)

The Uholka-Shyrokyi Luh massif is one of 8 extensive protected areas in the CBR. Located in central Transcarpathia, in the southwestern tip of Ukraine it belongs to the beech forest belt on the southern slopes of the Krasna mountain range. It spans from 400 to 1,400 m.a.s.l and encompasses the upper basin of the Luzhanka, Velyka Uholka, and Mala Uholka rivers (Brändli & Dowhanytsch, 2003). The Uholka-Shyrokyi Luh was initially established as a “strict nature reserve” in 1968 (Geyer *et al.*, 2009). It consists of two distinct administrative zones: Uholka in the south, situated next to the villages of Velyka Uholka and Mala Uholka, and the northern Shyrokyi-Luh, which is located around 12 km north of the Shyrokyi Luh village (Fig. 2). In 1992, the massif was declared a UNESCO-World Heritage Site. The total declared area of 11,860 ha, which includes 8,800 ha of natural old-growth forest, makes the Ukrainian Uholka-Shyrokyi Luh massif the largest continuous area of its kind in Europe (Brändli & Dowhanytsch, 2003; Commarmot, 2013).

Study area

The topography of the Uholka-Shyrokyi Luh massif is dominated by narrow valleys stretching across the landscape. The massif is characterized by fragmented relief, divided into narrow valleys formed by mountain streams. Geologically the massif is composed mostly of flysch formations of the Cretaceous and Paleogene periods with some Jurassic limestone, calcareous conglomerates, marls, and sandstone (Brändli & Dowhanytsch, 2003).

2.1.1 Climate

The Uholka-Shyrokyi Luh protected area lies in the Atlantic-continental climatic region of the Ukrainian Carpathians in the European temperate zone. The mean annual temperature measured at the meteorological station of the CBR in Uholka was 5.7°C. Mean temperature was highest in July with 16.2°C and the average January temperature was -6°C. The total mean annual precipitation was 948mm, with most of the precipitation occurring during the vegetation period (Brändli & Dowhanytsch, 2003). The Walter-Lieth climate diagrams reveal little risk of summer drought due to high precipitation during the summer months, an effect that is even more pronounced at higher altitudes (Fig. 3 b).

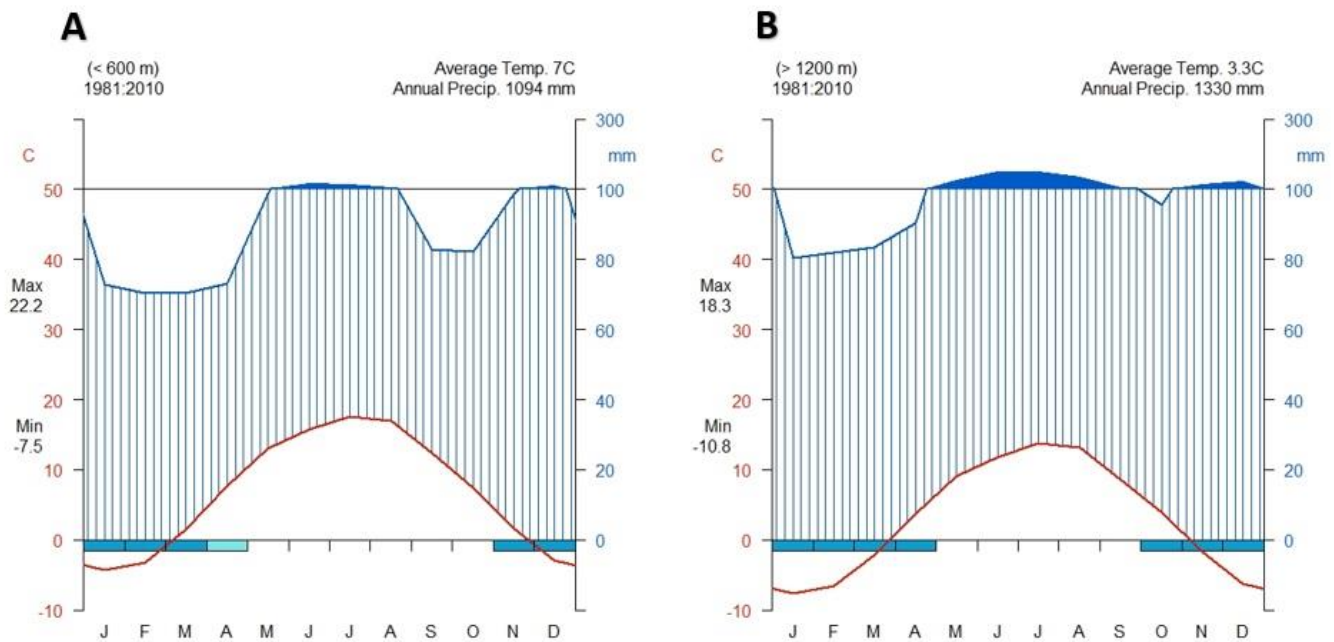


Fig. 3 Walter-Lieth climate diagrams for A low (<600 m.a.s.l.) and B high (>1,200 m.a.s.l) elevation plots.

2.1.2 Natural vegetation

Over 96% of the Uholka-Shyrokyi Luh protected area is covered with forests. Around 70 % of the forests are beech dominated communities including *Fagetum dentariosum* and *F. asperulosum*, forming a continuous belt from the lower altitudes up to the timber line. At lower altitudes oak species become more competitive and appear in mixtures more frequently. On more elevated and in wetter sites sycamore (*Acer pseudoplatanus* L.) competes well with beech. The Shyrokyi-Luh massif is slightly cooler, forming beech communities that are more frequently intermixed with Norway spruce (*Picea abies* H. Karst) and silver fir (*Abies alba* Mill.) (Brändli & Dowhanytsch, 2003).

2.1.3 Terrestrial sampling

In 2010 an inventory of the Uholka-Shyrokyi Luh massif was undertaken to assess forest structure and dynamics. A total of six survey teams conducted extensive terrestrial sampling over the entire Uholka-Shyrokyi Luh protected area. Using a non-stratified, clustered random sampling, clusters of two sample plots spaced at 100 m apart, were arranged on a systematic grid of 445m x 1,235m for a total of 353 circular plots of 500 m² (radius = 12.62 m) within the study area (Fig. 4). Thirty-nine plots were found to be outside the forested area, centered in a creek, inaccessible, or considered too dangerous for measurement. Hence, a total of 314 sample plots (145 in Uholka and 169 in Shyrokyi Luh) were fully assessed and were included in the analysis (Commarmot, 2013; Hobi *et al.*, 2015).

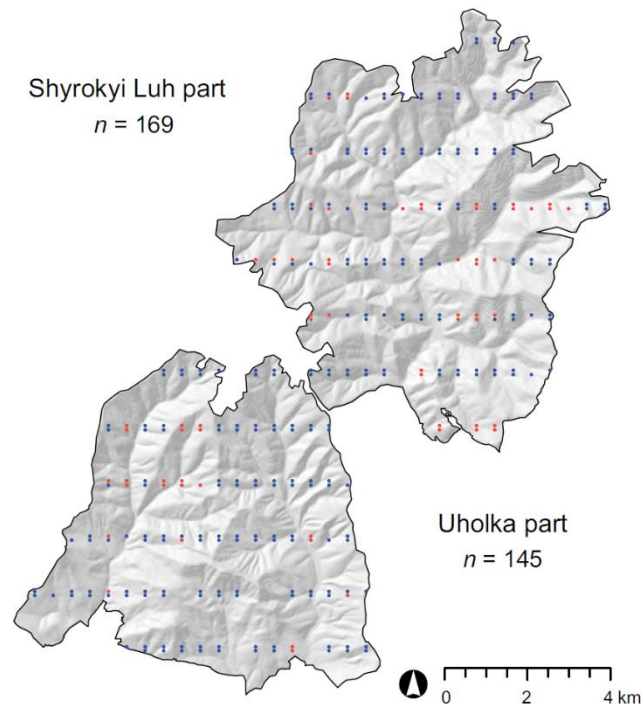


Fig. 4 Distribution of the sampling plots in the Uholka-Shyrokyi Luh massif. Blue dots represent the plots where an increment core was taken. Total number of plots assessed is shown for the two districts separately. Source: Hobi *et al.* (2015)

On each plot all living and dead trees with a diameter at breast height (DBH) above the threshold of 6 cm were recorded with an ID as well as a distance and an azimuth from the plot center. Further dendrological attributes such as DBH and tree species were also noted. Tree height, upper stem diameter 7m above ground, stem-form, and crown length were measured on a random sub-sample of the surveyed trees. In a circular 2,500 m² (radius = 28.2 m) interpretation area around the plot center the degree of crown cover and canopy closure were estimated as descriptors of the vertical and horizontal forest structure.

On 249 of the 314 sampled plots, an increment core was taken from one randomly selected tree with a DBH \geq 16 cm (Hobi *et al.*, 2015). Each core was taken between 80 to 100cm above ground and perpendicular to the slope of the terrain to minimize the presence of reaction wood in the core. Increment cores were glued on wooded supports and their surfaces were prepared using a core microtome (Gärtner & Nievergelt, 2010).

Tree rings of each core were measured with a LINTAB 3 digital positioning table (Rinntech, Germany) at a resolution of 0.01mm (Speer, 2012). The TSAP tree-ring software (Rinntech, Germany) was used for cross-dating. For increment cores that missed the pith, age was determined by a standard graphical method using sheets of concentric circles to estimate the number of missing rings between the pith and the first complete tree-ring (Duncan, 1989). To account for the number of years a tree takes to grow to the sampling height, 9 and 11 years were added to the cambial age for trees cored at 80 cm and 100 cm, respectively (Trotsiuk *et al.*, 2012).

3 Methods

3.1 Tree variables

Individual growth data was obtained from the increment cores collected, measured and crossdated by Martina Hobi during her PhD thesis. We received data containing information on the cored trees, containing the unique tree ID and other valuable information such as bark thickness and an estimate of tree age based on the measurements taken on the increment cores. It also provides the year until which an individual core was successfully cross dated, that allow for the selection of only the time periods when cross dating of the individual trees is considered accurate. We received plot-level data that included location of the plot and topographical features, as well as stand level forest attributes such as stem number, basal area, and standing wood volume. Furthermore, we were provided with a dataset containing the diameter and relative position of each tree in relation to the plot center given in distance and azimuth of each tree measured during the 2010 terrestrial inventory. From this data we were then able to estimate present levels of competition for each cored tree.

Due to low quality of the first increment core, on some of the 249 plots, additional cores were taken. To achieve a more homogenous sample structure only the best chronology of the cores on each plot was considered in further analysis leading to 249 cores assessed in our study. Because beech is a diffuse porous species and very shade tolerant, cross dating is notoriously difficult to do and prone to mistakes. Increment cores taken from beech often exhibit very narrow or even missing rings that make it difficult to match a year-ring to a specific calendar year (Grundmann *et al.*, 2008). This may result in the tree ring chronologies that can be safely dated back only to a specific year, where a problem arises. To avoid mismatches of tree-ring and climate data, the entire dataset was reduced to only the year rings that were considered as reliably cross-dated. For 48 of the 249 trees reliable cross-dating was not possible. Excluding these cores led to a sample of 211 cores with a total of 20,230 reliably cross-dated year-rings.

3.1.1 Tree-ring chronology development

Individual raw tree-ring width series were detrended using the `detrend` function from the `dpIR` package (Bunn, 2008). According to Fritts (1976) we applied conservative detrending by fitting a negative exponential curve to the individual growth-series. However, visual inspection of the negative exponential detrending procedure showed a complete mismatch, with most of the trees exhibiting increased tree-ring width with age rather than the expected decrease in tree-ring width over time. Therefore, this approach was discarded. As an alternative, we used a more flexible approach by using a cubic smoothing spline with a frequency response of 0.5 at two-thirds the length of the series (Cook & Peters, 1981). The standardized ring-width index (RWI) for each year-ring was then calculated by dividing the measured values by the corresponding value from the fitted growth curve.

Because of the geometrical constraints of increasing wood volume with increasing stem diameter, basal area increment (BAI) is a biologically more meaningful predictor of growth than tree ring width alone (Biondi & Qeadan, 2008). We computed BAI for each tree using the `BAI.out` function from the `dpIR` package. This function starts with a circular approximation of the basal area of the tree based on diameter measurements in the field, subtracts bark thickness, and then calculates yearly growth increment starting with the outermost ring. This approach showed more promising results than using the alternative `BAI.in` function due to many trees having rotten cores that hindered the assessment of the distance to the tree center (pith).

3.1.2 Competition index

To model inter-tree competition, we computed a competition index (CI) for each of the cored trees. For that purpose, several options for the competition index were considered. In their recent paper, Kahrman *et al.* (2018) distinguish between two main types of competition indices: distance-dependent and distance-independent ones. Distance-independent competition indices are not spatially explicit and can be seen as stand level attributes of the observed forest. However, distance-independent CI's such as stand-level basal area or stem number can only be used as a proxy for density if the stand is even-aged and dominated by horizontal competition. It also fails at representing small scale gaps or canopy openings and was therefore not further considered.

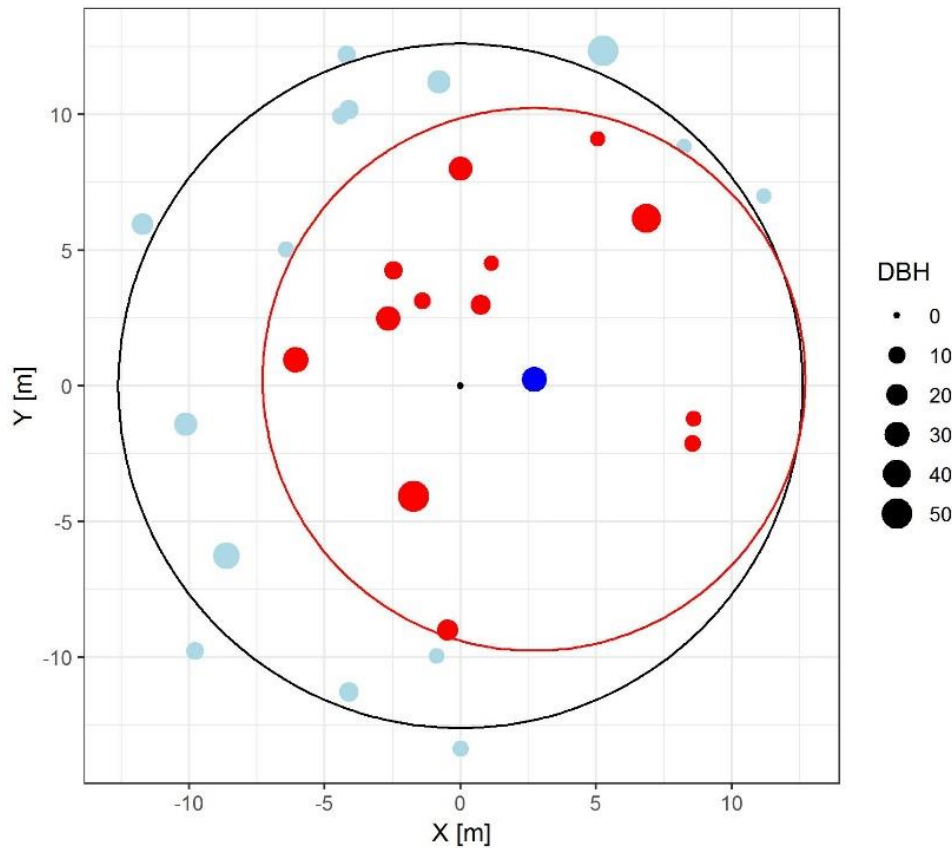


Fig. 5 Graphical representation of the procedure to calculate individual distance-dependent CI. The black dot represents the plot center with the black circle being the plot boundary. The dark blue dot is the focal tree with the competitor inclusion radius of 10 m shown as the red circle. Red dots are the included competitors. The size of the dots is proportional to the DBH (in cm).

Distance-dependent CI's are spatially explicit, different for each individual tree, and require knowledge of the distance between the focal tree and any potential competitor. They can further be subdivided into distance-dependent CI's with fixed or with a flexible competitor inclusion radius. Since the plots evaluated for this study were relatively small (radius of 12.6 m) and there was no information available about trees outside the plot boundary, we decided to use a fixed competitor inclusion radius approach. The CI proposed by Hegyi (1974) is defined as:

$$Eq. 1: CI = \sum_j \frac{DBH_j}{DBH_i} * \frac{1}{DIST_{ij}}$$

Where CI is the calculated competition index, DBH_j and DBH_i are the measured diameters at breast height of the competitors and the focal tree respectively, and DIST_{ij} is the distance between the centers of the two observed trees. It can be described as the sum of the distance weighted ratios of DBH of the focal tree and its respective competitors, and it is mostly based on the assumption that a large DBH implies high competitiveness, implying that large trees exert competitive stress on small neighboring trees. Since the cored trees were not necessarily close to the center of the plot, some of the trees had a competitor inclusion radius that partly overlapped the outside of the plot. In order to compensate for this shortcoming, we introduced a correction factor defined as:

$$\text{Eq. 2: } F_{corr} = \frac{A_p}{A_o}$$

Where F_{corr} is the correction factor, A_p is constant plot area of 500 m², and A_o is the area of overlap between the competitor inclusion radius and the plot boundary. For each plot, every individual tree was mapped using the `sp` package (Fig. 5). All neighboring trees inside the chosen competitor inclusion radius were matched and the distance to the focal tree was calculated. From the list of selected competitors, the CI was calculated according to Eq. 1 and subsequently multiplied with the area correction factor (Eq.2) in order to account for competitors potentially present outside the plot boundary.

To find the best possible competitor inclusion radius for further use, CI's were calculated for competitor inclusion radii of 4, 6, 8, 10, and 12 m. We then calculated Pearson's correlation coefficients of individual mean growth over the period of 1989-2009 and the competition values for each of the competitor inclusion radii. Correlation of growth to the calculated competition index increased with increasing competitor inclusion radius (Annex 1). However, since the 12m alternative was linked to considerable uncertainty stemming from some very high area correction factors, we decided to only consider the 10m radius CI in all further analysis.

3.2 Climate data

Two of the most widely used global gridded climate datasets are the WorldClim (Fick & Hijmans, 2017) and the CRU TS (Harris *et al.*, 2014) datasets. However, these differ strongly in data quality and availability over space and time. The WorldClim dataset provides climatic means of a reference period (1960-1990) at medium to high spatial resolution (30 arc sec or ca. 1-km resolution). Since these climatologies are neither available in yearly nor monthly resolution, they were not suitable for calculating growth-climate relationships. The CRU TS dataset, on the other hand, includes monthly climate data (1901 to the present day) at a 0.5° resolution (~50x50km). This low spatial resolution strongly limits the representation of spatio-temporal processes at a local scale. Since many of the sampled forest plots would lie on the same raster pixel, climatic differences between plots would have been ignored. To bridge the gap between spatial and temporal resolution, some recent databases use interpolation and a combination of datasets to downscale local climate.

The EuMedClim dataset combines the WorldClim and the CRU TS dataset into a new dataset that provides climate series at high spatial and temporal resolutions (30 arc sec or ca. 1-km resolution), including monthly, seasonal, and yearly time steps of climate series across Europe and the Mediterranean Basin (Fréjaville & Benito Garzón, 2018). EuMedClim data is freely available (<http://gentree.data.inra.fr/>) as gridded yearly data from 1901 to 2014 for each of the 21 climatic variables.

The CHELSAcruts dataset provided by the Swiss Federal Institute for Forest, Snow, and Landscape Research (WSL), offers three climatic variables: monthly precipitation, monthly mean of daily minimum Temperature, and monthly mean of daily maximum temperature in a 1km spatial resolution (Karger *et al.*, 2017). All climatic variables are available in a monthly resolution and directly downloadable (<http://chelsa-climate.org/downloads/>) in Tiff-format. Since many of the climatic variables now also provided by the EuMedClim database were not yet available at the beginning of this study, the CHELSAcruts dataset was deemed most suitable for our analyses

Using the R statistical language, the entire CHELSAcruts dataset was downloaded for the period 1901 to 2009 (3924 climate layers: 109 years * 12 months * 3 variables). Because of the file size of around 100Mb for each of the climate layers, each individual layer was downloaded and while in memory, cropped to the extent of the relevant Ukrainian district, effectively reducing the size of the entire dataset to less than 200Mb. The climate data was subsequently loaded into R as a raster-stack using the `raster` package. Since the center coordinates of the plots were provided in UTM 34, they were transformed into a Spatial-Points-object and then projected to WGS 84 to match the projection of the climatic data. To extract the climate time series for each individual plot we used the `extract` function from the `raster` package. Since this operation proved to be computationally intensive, each of the raster layers was transformed into one row of a large matrix. By creating an ID-raster-stack, with the same extent as the original raster, and applying the `extract` function to the ID-raster-stack, we extracted the ID of the climate variables. We were then able to extract the climate data from the matrix by tabular indexing in a more efficient way. Climate data was merged with the tree data based on the individual ID and then restructured using the `dplyr` package in order to have each row represent one single year with all variables as columns.

To assess the influence of water deficits on radial growth we computed the monthly Climatic Water Balance (CWB) for each plot. To estimate the monthly potential evapotranspiration, we used the *Hargreaves* function from the *SPEI* package. Using latitude as a proxy for radiation, the *Hargreaves* function provides an estimate of monthly potential evapotranspiration based on monthly minimum and maximum temperatures and a vector of monthly precipitation (H. Hargreaves & Samani, 1985). Monthly climatic water balance was then calculated as:

$$\text{Eq. 3: } CWB = P - ETO$$

Where CWB is the monthly Climatic Water Balance, P is the monthly precipitation sum, and ETO is the monthly potential evapotranspiration as calculated with the *Hargreaves* function.

3.3 Statistical analysis

All statistical analyses were performed using the R software for statistical computing, version 3.5.1 (R Core Team, 2017). The trends in the climate data were assessed for the periods of 1901-2009 and 1981-2009 using the nonparametric Mann-Kendall trend-test as provided by the *zyp* package. The overall growth-trend was assessed by plotting annual means of tree-ring width and basal area increment. Trends were assessed for the periods of 1900-2009 and 1981-2009 using the Mann-Kendall trend-test. To evaluate the age effect on radial growth, we realigned growth values according to their cambial age and calculated mean growth values for each 1-year age class. Trends in mean growth were then assessed using the Mann-Kendall trend-test.

Since it was not possible to compute past competition – as this would have required increment cores from all competitors – we assumed little to no changes in competitive status of trees over the last 20 years (1989 - 2009). This timespan was chosen as a trade-off between consistency of the competition index and sample size and all further calculations involving competition refer to the period 1989 - 2009. We then calculated mean BAI values of each individual tree over the timespan and applied linear regression to the log-transformed growth values and the CI. Following the methodology proposed by Piutti and Cescatti (1997), we defined the intercept of the regression line as corresponding to a value for average growth under ideal circumstances (i.e., no competition). For repartition into the two competition classes we applied a threshold to the CI-value corresponding to a mean growth decrease of 50 % due to competition and the data was attributed to the “Low” (CI ≤ 1.35, n = 151), or “High” (CI > 1.35, n = 60) competition classes.

To select the most meaningful variables for the mixed effects models, we calculated 1000-fold bootstrapped Pearson’s correlation coefficients for each of the climatic variables using the *dcc* function of the *treeclim* package (Zang & Biondi, 2015). Correlation coefficients of BAI and the monthly (July of the year prior to ring formation to September of year of ring formation), as well as seasonal climate (previous Summer, previous Fall, Winter, Spring, and one additional Summer) were computed for each core individually. The correlation coefficients were then plotted as boxplots to select the variables with the strongest influence on growth for further analysis. Using the same approach, we calculated individual correlation coefficients for the period of 1989-2009 and plotted boxplots illustrating the distribution of individual correlation coefficients within each of the two competition subgroups.

We used linear mixed effects modelling to quantify the effects of climate, tree size, competition, and their interactions on growth. Following the methodology proposed by Zuur *et al.* (2009) we started by building a model containing a selected set of predictors as fixed effects. Variable selection was done based on the results of the correlation analysis and the correlations between the climatic variables. Since the effect of competition on the climate-growth relationship was more pronounced in the seasonal climatic variables than in the monthly values, we only integrated the seasonal values in the model. The final model was:

$$\text{Eq. 4 } \log(\text{BAI} + 1) \sim \alpha + \beta_1(\text{Size}) + \beta_2(\text{CWB}) + \beta_3(\text{Tmax}) + \beta_4(\text{Size}) \times (\text{CWB}) + \varepsilon$$

Where α is the intercept, ε represents the error term, and β_{1-4} are the parameters of the fixed components namely, tree size, climatic water balance, maximum temperature and an interaction term linking tree size to the climatic water balance. Specifically, we used spring climatic water balance, climatic water balance of two most recent summers, winter, spring and summer maximum, temperature as well as summer maximum temperature of the year prior to ring formation. To determine the relative effect strengths of the modeled climatic variables climatic variables were centered and scaled prior to the analysis. We fitted the model over the entire period where climate data was available (1901-2009). To find the ideal random structure we built two versions of model with the same fixed structure. One was built using the `gl` function and included only the fixed components, while the other was constructed using the `lme` function from the `lme4` package and included a random factor for `treeID`, which allowed for an individual intercept of each increment core (Bates *et al.*, 2015). Models were fitted using restricted maximum likelihood (REML). We then compared the Aikake Information Criteria (AIC) – defined as twice the difference between the value of the likelihood (measure of fit) and the number of parameters (the penalty for model complexity) – of the two models in order to select the best random structure (Zuur *et al.*, 2009). The random intercept models were superior to the generalized linear models and were selected for further analysis. To check for changes in climate response, we then refitted the same model including only the most recent 20 years (1989-2009). We then modeled the subsets of low- and high- competition trees over the period of 1989-2009 separately to check for differences in growth response between competition classes. Finally, we calculated the marginal R^2 (proportion of variance explained by the fixed terms) and the conditional R^2 (proportion of variance explained by the combination of fixed and random terms) from the final model objects using the `r.squaredGLMM` function from the `MuMin` package according to Nakagawa and Schielzeth (2013).

4 Results

4.1 Growth trend

Over the last 100 years mean tree-ring growth has significantly increased across the study area (Fig. 6a). The growth trend reveals an increase in mean tree-ring width of 0.358mm over the last century. However only 27% of individual trees showed a significant ($p < 0.05$) increase in growth time. Over the climatic reference period of 1981-2009 the slope was even stronger, however not significant. The trend in BAI was also evident. Mean basal area increment of trees has increased by 16.3cm² over the period of 1901-2009 (Fig. 6b). The highly significant trend suggests that mean BAI of trees in study area has more than doubled over the last century. 62 % of trees exhibited a significant positive growth-trend. The trend over the last 30 years failed to achieve significance but also indicates increasing growth rates.

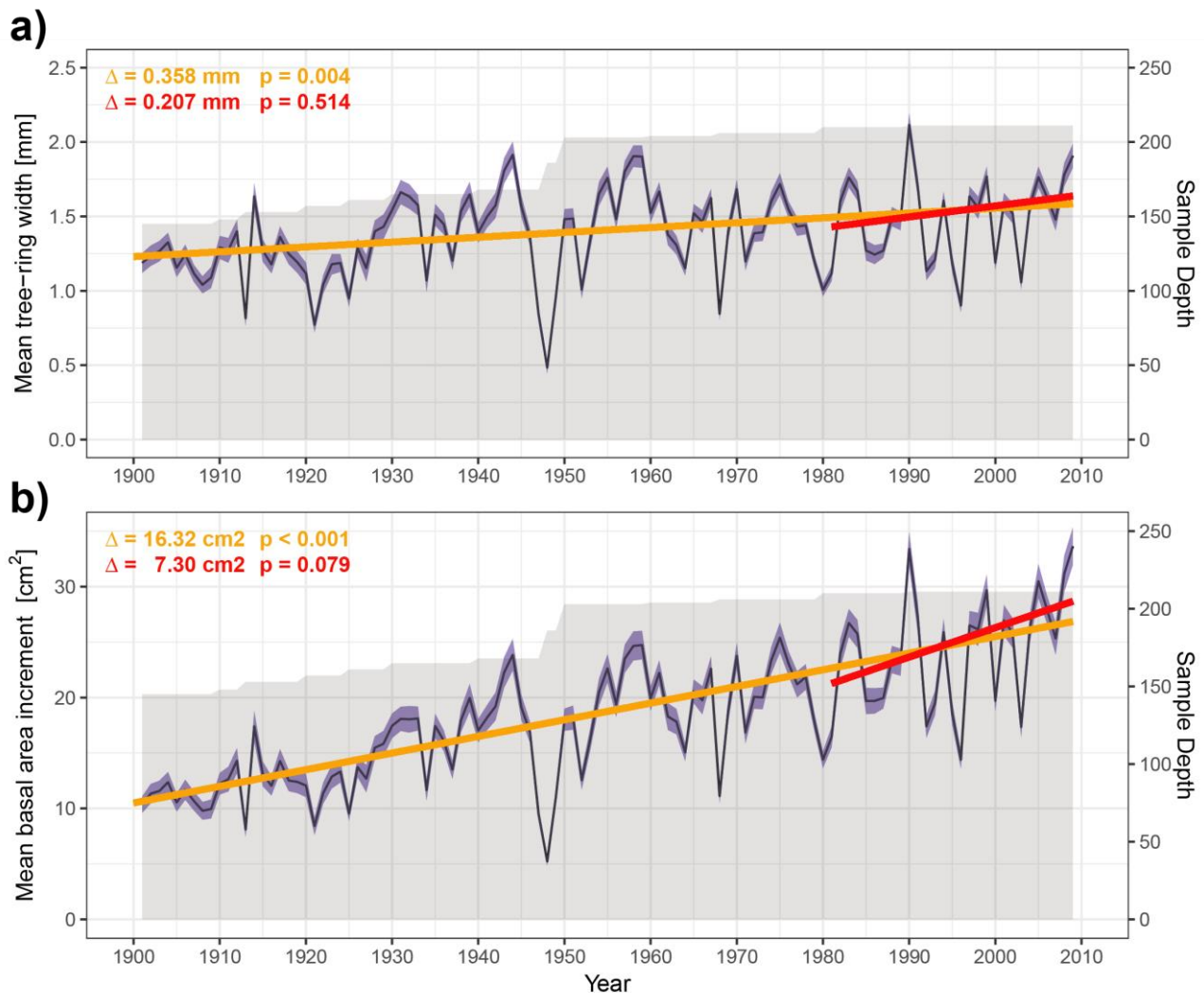


Fig. 6 General trend of **a)** mean tree ring width and **b)** basal area increment. Black lines represent mean growth per year, with the standard error as blue ribbons (not displayed when sample depth ≤ 1). The gray areas represent sample depth. Orange (and red) lines are the trend lines over the period of 1900 - 2009 (and 1981 - 2009), respectively. Estimated changes in mean growth over the entire period and significance values of the growth trends are displayed in the upper left corners.

4.2 Age trend

When plotting individual tree growth in relation to cambial age (age of the year-ring), the effect is reduced. One can observe the typical elevated growth values in juvenile trees with the associated rapid decline over the first 60 to 70 years followed by a long period of relatively stable growth (Fig. 7a). Interestingly, after a short growth depression at ages of 280-300 years, growth continues at similar levels up to very old ages.

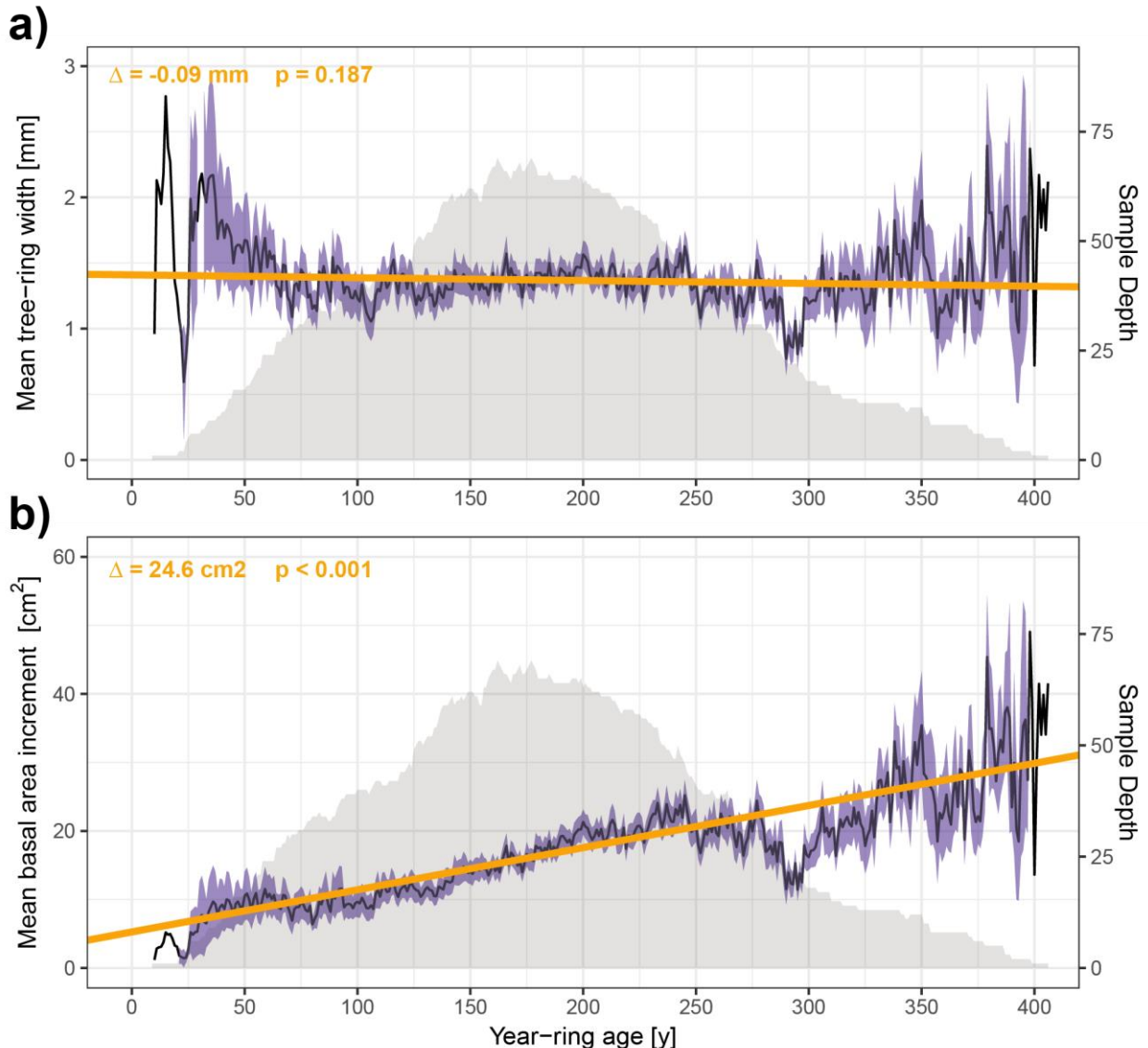


Fig. 7 General trend over year ring age in **a)** mean year ring growth and **b)** basal area increment. Black lines represent mean growth per year, with the standard error as blue ribbons (not displayed when sample depth ≤ 1). The gray areas represent sample depth. Orange (and red) lines are the trend lines over the period of 1900 - 2009 (and 1981 - 2009), respectively. Estimated changes in mean growth over the entire period and significance values of the growth trends are displayed in the upper left corners.

Cambial age was linked to a highly significant increase in BAI suggesting that older trees grow faster than younger trees. However, due to the high correlation of tree age and size (Annex 2), as well as the geometrical constraints of volumetric growth it is difficult to separate the effect of age from the inherent effect of tree size on basal area increment.

4.3 Climate trends

The trend lines for mean monthly maximum temperature reveal an increase of 0.42°C over the period of 1901-2009 and an increase of 1.5°C over the period of 1981-2009 (Fig. 8a). Annual precipitation sum decreased by 23mm over the entire period, but this trend was not significant. Over the last thirty years precipitation significantly increased by more than 180mm (Fig. 8b). The trend in climatic water balance closely resembled the pattern in precipitation sum (Fig. 8c). CWB decreased by 18mm over the period of 1981-2009 but increased by 116 mm over the last thirty years, though none of these trends were significant.

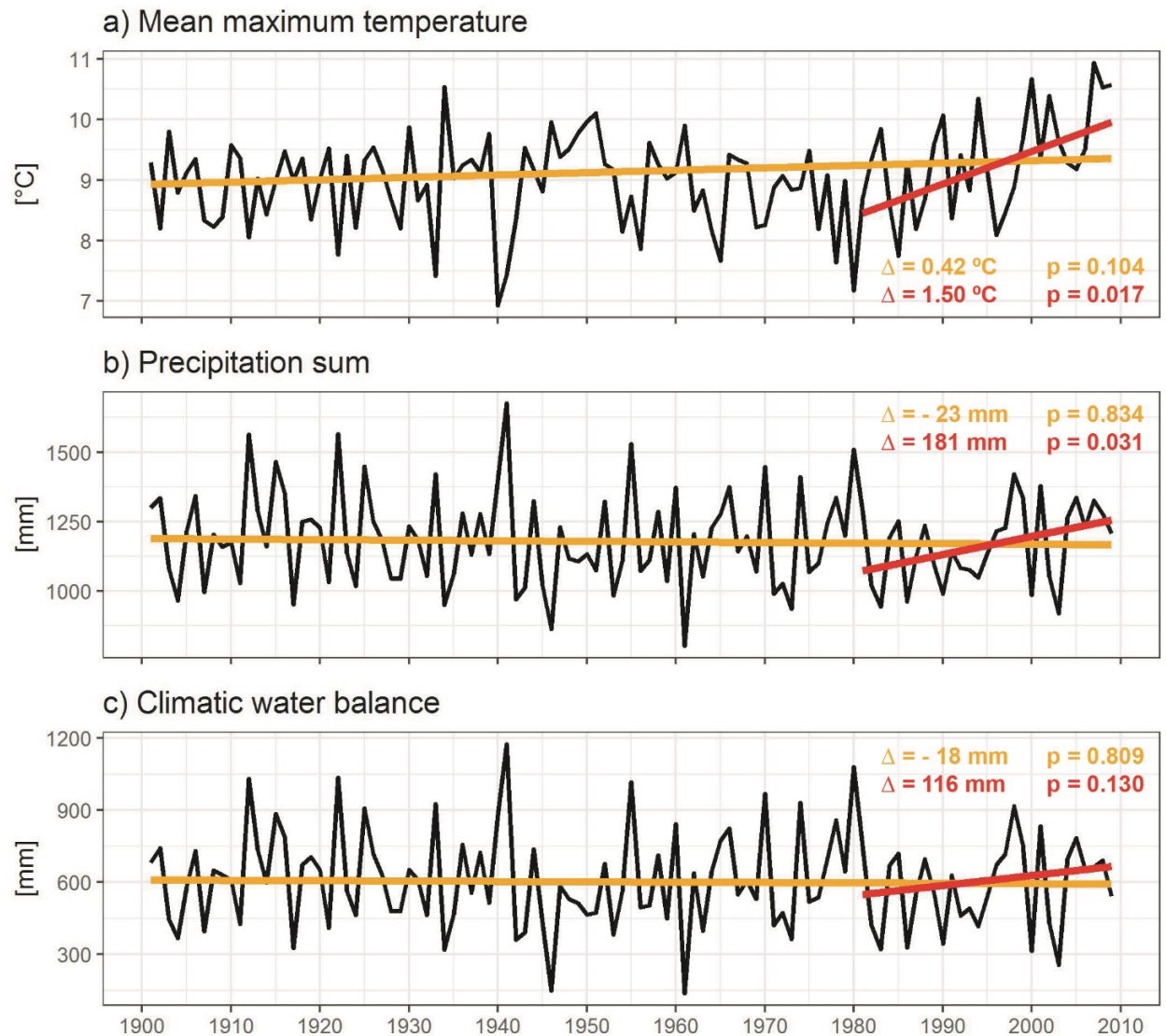


Fig. 8 Time-series of **a)** annual mean maximum temperature, **b)** precipitation sum and **c)** climatic water balance for the period 1901-2009. Black lines are the yearly mean value over all plots. Orange (and red) lines are the trend lines over the reference period of 1901-2009 (and 1981-2009), respectively. Absolute changes over the respective periods and p-values are indicated on the right side.

4.4 Growth-climate relationships

Maximum temperature from previous October to February as well as June maximum temperature was positively correlated to radial growth, whereas maximum temperature of the previous September showed the inverse effect (Fig. 9a). The distribution of the Pearson's correlation coefficients reveals high variability in individual tree response to climate.

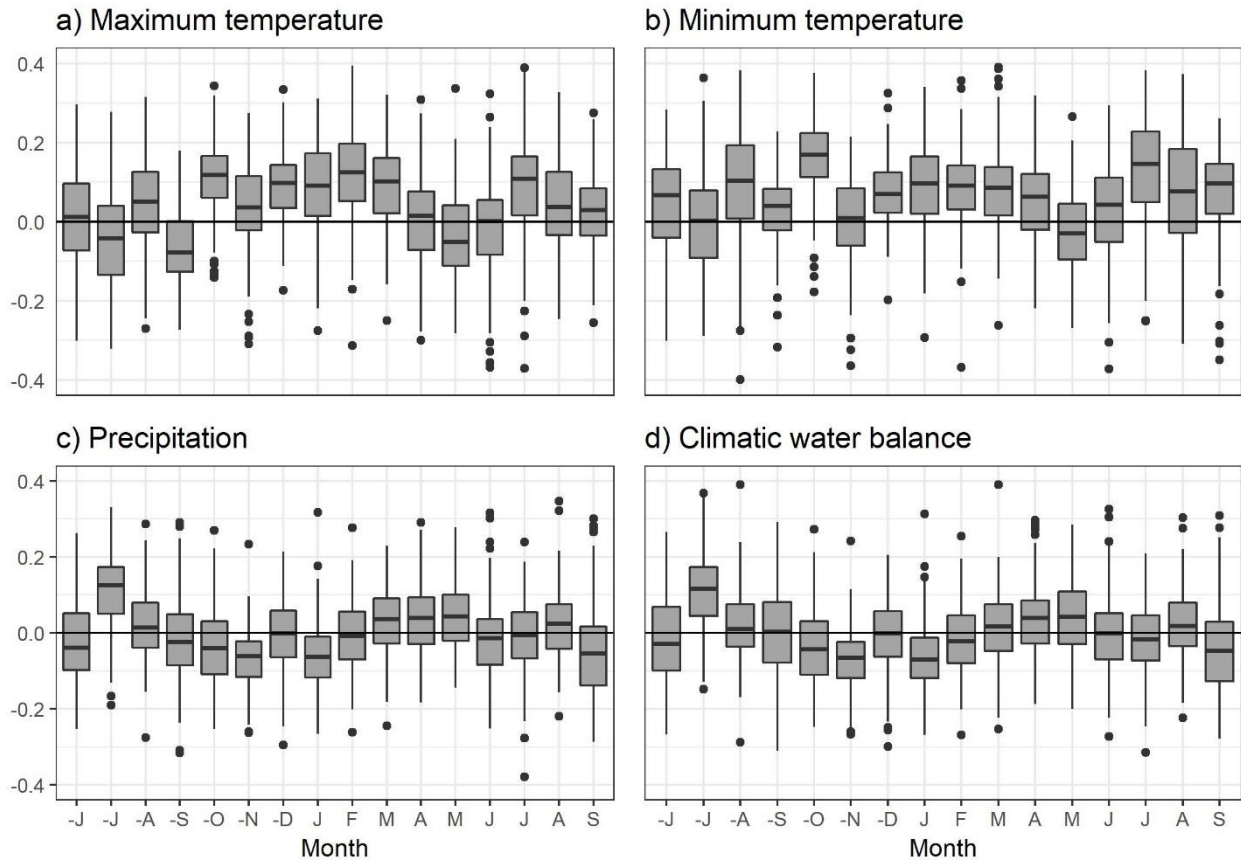


Fig. 9 Boxplots of the bootstrapped correlation coefficients of basal area increment chronologies and **a)** mean monthly maximum temperature, **b)** mean monthly minimum temperature, **c)** precipitation and **d)** climatic water balance. Months considered were June prior to ring formation (-J) to September (S) of the year of ring formation for the period 1901 – 2009. Boxes represent the interquartile range and whiskers represent the upper and lower quartiles of the distribution. Outliers are represented as points.

Tree growth over the period 1901-2009 was relatively insensitive to precipitation. July precipitation of the year before ring formation was positively correlated to BAI (Fig. 9c). November and January precipitation were negatively correlated to radial growth. Correlation patterns found between tree growth and the climatic water balance were similar to the ones observed for precipitation. No immediate detrimental effect of drought could be detected as correlations to CWB were generally low during the summer months (Fig. 9d).

Over the period 1901–2009, at the seasonal scale, elevated maximum and minimum temperatures had a generally positive effect on growth (Fig. 10a & 10b). Maximum winter temperature had the strongest effect and positively influenced radial growth. Except during the winter months, minimum temperature appeared to have a stronger influence on radial growth than maximum temperature.

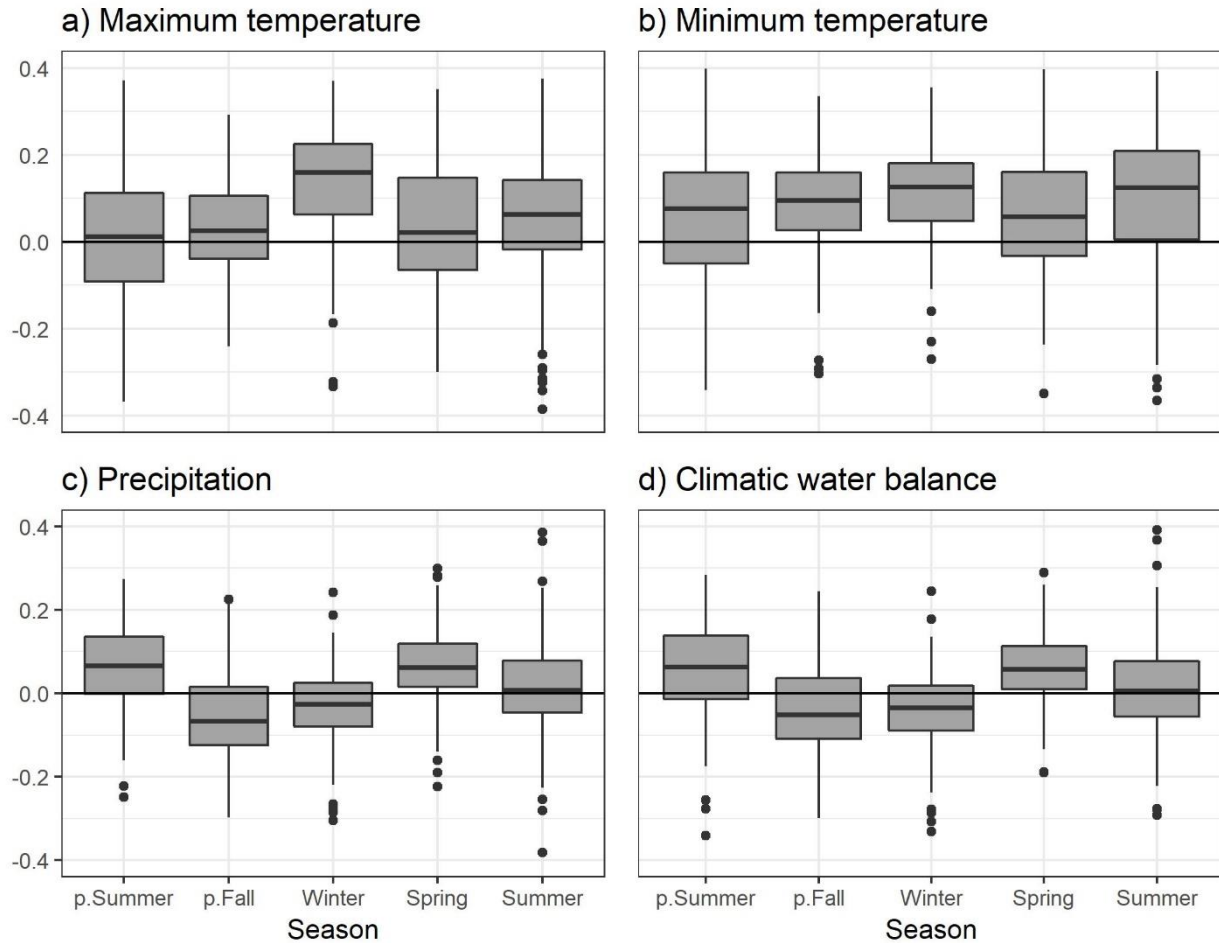


Fig. 10 Boxplots of the Pearson's correlation coefficients between BAI and seasonal climate. **a)** maximum and **b)** minimum temperature, **c)** precipitation and **d)** climatic water balance for previous summer (June, July, August), previous fall (September, October, November), winter (December, January, February), spring (March, April, May) and summer (June, July, August) for the period 1901–2009. Boxes represent the interquartile range and whiskers represent the upper and lower quartiles of the distribution. Outliers are represented as points.

Growth response to precipitation and the CWB exhibited similar behaviour. Summer precipitation of the year before ring formation and spring precipitation during the growth year were both positively correlated to growth. Surprisingly, there was no clear correlation between growth and summer precipitation or CWB, suggesting that tree growth in the study region is less limited by summer drought than anticipated. The low correlation coefficients (mean < 0.2 for all climatic variables) illustrate that tree growth over the period of 1901–2009 was marginally sensitive to climate.

4.5 Effect of competition on growth

Competition had a significant negative impact on mean basal area increment. The exponential decay fit indicates that trees experiencing less competition tend to grow more vigorously (Fig. 11). Mean growth under no competition (y-intercept) was estimated to be 34.7 cm² per year. The threshold for the distinction of the two competition classes was set at a CI-value of 1.35, corresponding to a mean annual growth of 17.4 cm² per year, or equivalent to 50% of the growth potential (expected growth under no competition).

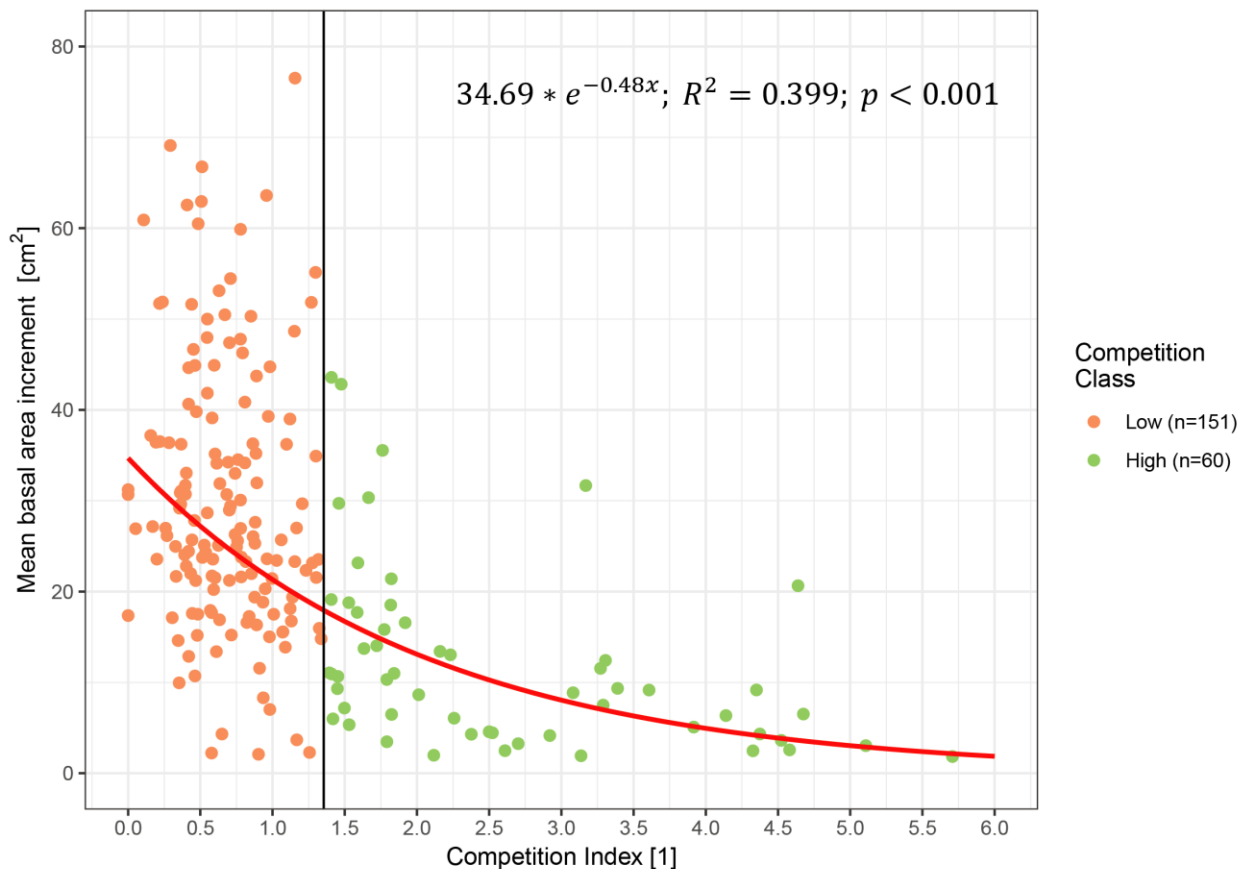


Fig. 11 Mean BAI of the cored trees for the period 1989-2009 in relation to the level of competition experienced. The red line is the regression line with its y-intercept representing expected mean growth under no competition. The vertical line is the cutoff for the competition classes, intersecting the regression line at 50% of potential growth. The equation, the R²-value and p-value are indicated in the upper right corner. Note that 5 points with very high CI's are not shown in the graph.

Mean DBH of trees under high competition was lower than of the trees under low competition. Trees under strong competition not only grew less vigorously but were also generally younger and smaller than trees experiencing low levels of competition (Table 2).

Table 1 Variability of tree attributes among the 211 cored trees and within competition classes, showing the mean (bold) and standard deviation, of DBH, Age, Competition Index (CI) and basal area increment (BAI).

Group	Sample Size	DBH [cm]	Age [y]	CI [1]	BAI [cm ²]
All	211	55.5 ± 20.1	228 ± 77	1.36 ± 1.67	25.1 ± 15.8
Low Competition	150	63.5 ± 16.0	260 ± 63	0.68 ± 0.32	30.0 ± 12.6
High Competition	60	35.4 ± 14.3	172 ± 66	3.06 ± 2.37	12.7 ± 10.8

4.6 Effect of competition on climate sensitivity

Since the competition status of trees was assumed to remain unchanged over the last 20 years, the growth-climate relationship was reassessed for the period 1989–2009 for trees experiencing high and low competition separately (Fig. 12). The observed patterns closely resemble the patterns observed over the period 1901–2009. Maximum July and September temperatures in the year before tree-ring formation were negatively correlated to growth. Elevated May, June, and August temperatures were also associated with narrow rings, whereas growth was positively correlated to October through March temperatures. Precipitation from February through August was positively correlated to basal area increment.

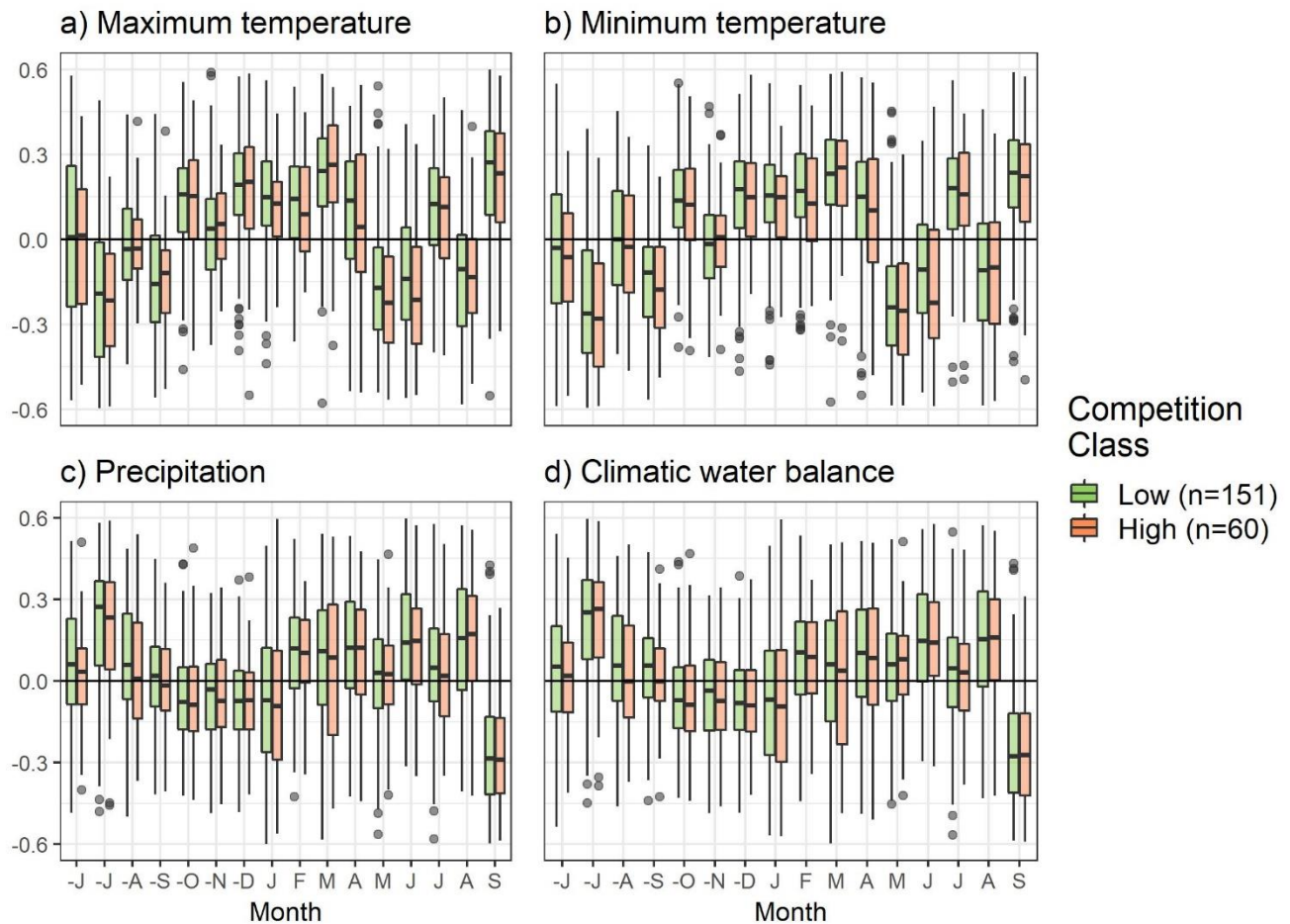


Fig. 12 Boxplots of the correlations of basal area increment chronologies and **a)** mean monthly maximum temperature, **b)** mean monthly minimum temperature, **c)** precipitation and **d)** climatic water balance. Months considered were June prior to ring formation (-J) to September (S) of the year of ring formation for the period 1989–2009. Correlations were calculated independently for each competition class. Boxes represent the interquartile range and whiskers represent the upper and lower quartiles of the distribution. Outliers are represented as points.

Results

Examination of the seasonal correlations returned similar results (Fig. 13). Mean maximum summer temperature of the year prior to ring formation was negatively correlated to BAI, whereas elevated winter and spring temperatures had the opposite effect. Trees under high competition appeared to be less sensitive to spring temperature than trees experiencing low levels of competition but were adversely affected by elevated winter climatic water balance.

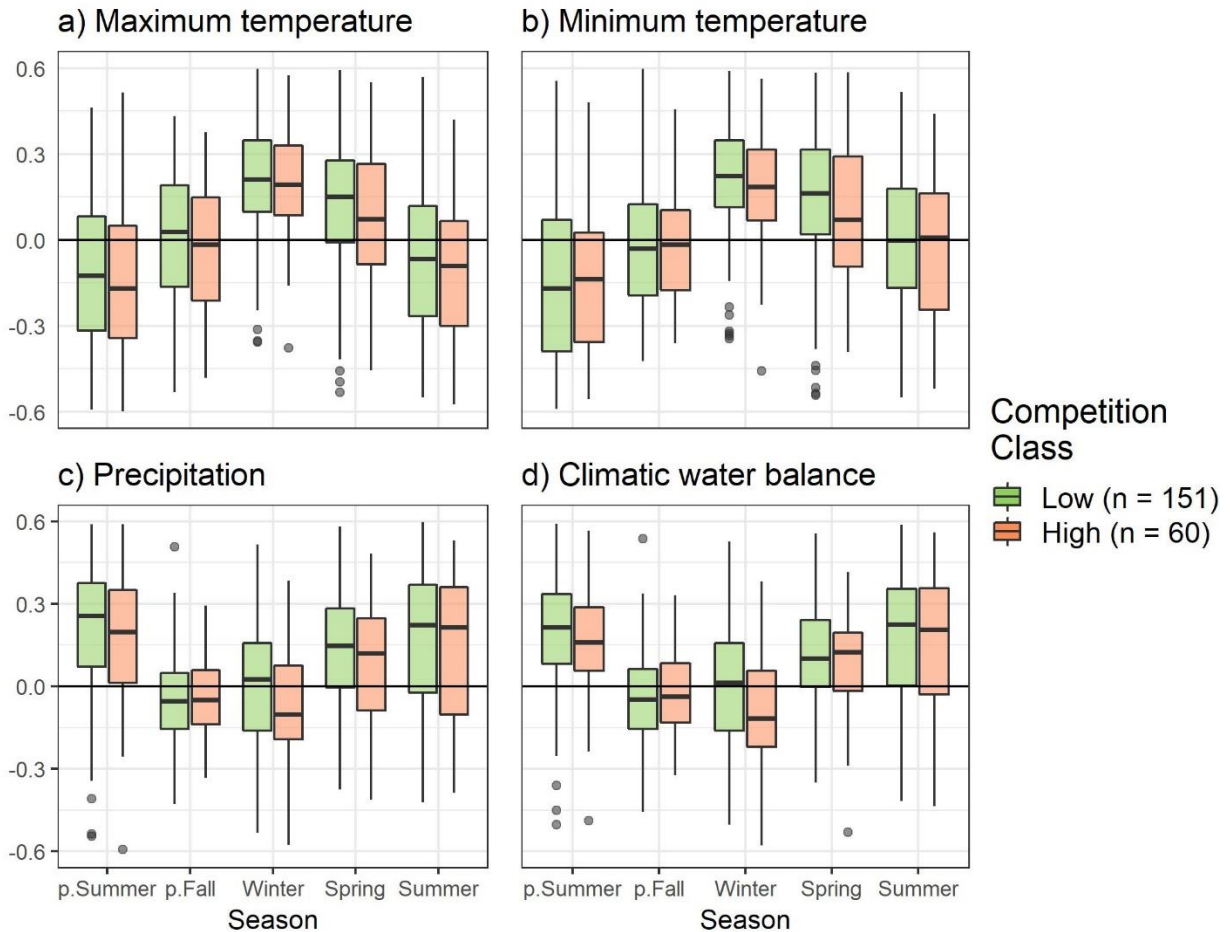


Fig. 13 Boxplots of the correlations between individual basal increment chronologies and seasonal climate (a) maximum and b) minimum temperature, c) precipitation and d) climatic water balance) for previous summer (June, July, August), previous fall (September, October, November), winter (December, January, February), current spring (March, April, May) and current summer (June, July, August) for the period 1989–2009. Correlations were calculated independently for each competition class. Boxes represent the interquartile range and whiskers represent the upper and lower quartiles of the distribution. Outliers are represented as points.

4.7 Mixed effect models

The results of the linear mixed-effects models show that DBH was the most influential factor in predicting basal area increment. The models generally agree well with the results of the correlation analysis. Tree growth significantly increased with tree size across all subsamples (Table 2). Maximum temperature of the summer before year ring formation was not a good predictor of tree growth, failing to achieve significance in any of the subgroups. Elevated winter temperatures were associated with a significant increase in basal area increment across all modeled groups. Spring CWB had a significant positive effect on tree growth over the period 1901-2009 but showed the opposite effect for the period 1989-2009. Similarly, summer CWB was negatively correlated to growth over the entire period, while over the last 20 years, the opposite was true, pointing to a change in climate response. There was a significant interaction between DBH and summer climatic water balance, indicating that larger trees benefit more from elevated water availability during summer than smaller trees.

Table 2 Summary of the fitted linear mixed-effects showing the effect of size and climate on log transformed basal area increment of all trees from 1901 to 2009, as well as for all trees and the two competition subgroups for the period 1989-2009.

Group	Marginal R ²	Conditional R ²	Fixed effect*	Estimate	SE	df	t-value	p-value
All (1901-2009)	0.417	0.602	Intercept	7.088	0.0329	19853	215.25	<0.001
			dbh	0.7051	0.0104	19853	68.00	<0.001
			PsumTmax	0.0024	0.0099	19853	0.24	0.813
			winTmax	0.0282	0.0058	19853	4.88	<0.001
			sumTmax	0.0243	0.0101	19853	2.41	0.016
			PsumCWB	0.0233	0.0072	19853	3.24	0.001
			sprCWB	0.0496	0.0057	19853	8.63	<0.001
			sumCWB	-0.0218	0.0074	19853	-2.96	0.003
			dbh:sumCWB	0.0119	0.0054	19853	2.22	0.026
All (1989-2009)	0.424	0.784	Intercept	7.089	0.0496	4210	142.90	<0.001
			dbh	0.6800	0.0418	4210	16.28	<0.001
			PsumTmax	-0.0279	0.0196	4210	-1.42	0.154
			winTmax	0.1080	0.0099	4210	10.86	<0.001
			sumTmax	-0.0832	0.0205	4210	-4.05	<0.001
			PsumCWB	0.0635	0.0145	4210	4.38	<0.001
			sprCWB	-0.0292	0.0120	4210	-2.43	0.015
			sumCWB	0.0466	0.0159	4210	2.93	0.003
			dbh:sumCWB	0.0193	0.0080	4210	2.40	0.016
Low Competition (1989-2009)	0.272	0.713	Intercept	7.288	0.0682	3011	106.90	<0.001
			dbh	0.5131	0.0536	3011	9.57	<0.001
			PsumTmax	-0.0074	0.0224	3011	-0.34	0.742
			winTmax	0.1166	0.0112	3011	10.38	<0.001
			sumTmax	-0.1013	0.0233	3011	-4.34	<0.001
			PsumCWB	0.0920	0.0166	3011	5.54	<0.001
			sprCWB	-0.0223	0.0136	3011	-1.64	0.102
			sumCWB	0.0712	0.0206	3011	3.45	<0.001
			dbh:sumCWB	-0.0059	0.0112	3011	-0.53	0.600
High Competition (1989-2009)	0.388	0.748	Intercept	7.110	0.1015	1191	70.03	<0.001
			dbh	0.9576	0.1122	1191	8.54	<0.001
			PsumTmax	-0.0621	0.0403	1191	-1.54	0.123
			winTmax	0.0856	0.0204	1191	4.19	<0.001
			sumTmax	-0.0206	0.0420	1191	-0.49	0.623
			PsumCWB	0.0050	0.0292	1191	0.17	0.863
			sprCWB	-0.0505	0.0244	1191	-2.06	0.039
			sumCWB	0.0633	0.0330	1191	1.92	0.055
			dbh:sumCWB	0.0273	0.0239	1191	1.15	0.252

* dbh, tree size; PsumTmax, summer maximum temperature of the previous year; winTmax, maximum winter temperature; SumTmax maximum summer temperature; Psum-, spr- and sum-CWB represent climatic water balance of the previous summer, current spring and current summer, respectively; dbh:SummerCWB represents the interaction terms for size and summer climatic water balance.

Results

As indicated by the low p-values, maximum summer temperature and CWB of the last year were not good predictors of tree growth for trees facing high levels of competition, however they were highly significant across the low competition sample. Except for a stronger negative reaction to high spring CWB, trees of the high competition subgroup appeared to be less sensitive to climate. Among the competition subgroups, the size-CWB interaction failed to achieve significance.

As indicated by the marginal R^2 values, the fixed components of the linear mixed-effects models linking growth to tree size and climate, explained 0.27 to 0.42 of total variance. Including the random effect significantly increased model fit (REML comparison, p-value < .001). The mixed effects models explained 0.60 to 0.78 of the variances in tree growth when considering the random effect (conditional R^2) and highlighted the importance of including the individual tree responses when modelling tree growth.

5 Discussion

Our results indicate a continuous increase in mean radial growth over the period of 1901-2009. The plausibility of this growth trend is underlined by observations made by researchers in different forests throughout Europe. Pretzsch (1999) found that, especially at lower altitudes, forest inventories and growth trend studies frequently reveal an increase in productivity of European forests since the middle of the last century. Other recent studies also point to an increase in growth of beech trees over the last century in stands across north eastern France (Bontemps *et al.*, 2009; Charru *et al.*, 2010; Bontemps *et al.*, 2012). Another study found accelerating stand growth dynamics over the last century. Researchers observed increased diameter and volume growth, following similar allometric rules but progressing faster in their development (Lebourgeois *et al.*, 2005; Pretzsch *et al.*, 2014).

The observed trend may have several causes. Firstly, the trend may be related to the size-growth relationship, with tree ring width peaking at an early age and basal area increment peaking during maturity. Peak basal area increment growth may additionally be delayed by primeval forest dynamics, where regeneration takes place under small canopy openings with limited light and young beech trees may endure long suppression times until they reach the upper canopy and can grow at their full potential (Packham *et al.*, 2012). The relationship between tree size and age is defined by the regime of silviculture interventions or natural disturbances in managed- and natural- forests respectively. In typical managed forests the age-size relationship is usually strong as equally aged trees within a stand face similar conditions in terms of not having to endure long suppression times under a dense canopy. Therefore, the age-size relationship can be a useful descriptor of the “naturalness” of forests where natural forests tend to have relatively weak age-size relationships. For our sample of trees where age estimation was successful, age only explained 31% of the observed variance in DBH illustrating the primeval nature of these forests. The finding that even very old beech trees (> 300 years) can still exhibit similar growth rates than far younger trees of equal size a useful observation for improving our understanding of forest ecology.

Secondly, the observed trend in growth may be caused by climate change. Rising temperatures combined with sufficient precipitation often result in increased tree growth (Grundmann *et al.*, 2008). The climate time-series show a clear increase in air temperature over the last century and an even stronger one over the last 30 years. Rising temperatures may have induced a steady increase in tree growth since the early 20th century, with a rapid increase in the last 20-30 years. Our results show that high winter temperatures significantly increased radial growth of beech, possibly explaining a proportion of the observed growth trend. Beech is susceptible to leaf damage caused by late frosts, resulting in narrower tree-rings in years with strong late frost events (Dittmar *et al.*, 2006). Elevated temperatures may therefore additionally benefit beech trees by reducing the frequency of damaging frost events. As a result, climate change may give beech the competitive advantage necessary to achieve dominance on new sites in the Carpathians previously considered too cold or too wet. Other factors, such as CO₂- and N-deposition might also play a role in increasing growth rates, but moisture availability has normally a stronger influence on tree growth than CO₂ and N-deposition (Levesque *et al.*, 2017).

Tree size was the most influential variable in predicting basal area increment. Removing the DBH at the year of ring formation from the models resulted in very low values of explained variance by the climate data alone. The low correlation of growth and climate suggest that the growth of European beech in primeval beech forests of Eastern Ukraine is marginally sensitive to climate. In our study, winter temperature was the most influential climatic predictor of growth. Over the period of 1901-2009 tree growth was positively correlated to summer temperatures and exhibited a negative response to the summer climatic water balance. These findings are surprising considering that the sensitivity of beech to drought is well documented (Jump *et al.*, 2006; Friedrichs *et al.*, 2009; Roibu *et al.*, 2017). Analysis of the two last decades revealed, that high summer temperatures and limited moisture availability now have a detrimental, however not significant, effect on tree growth. These findings suggest, that drought may have become an increasingly important factor in determining growth.

Elevated levels of competition were linked to a lower mean growth over the last 20 years. Because of high correlations between tree size and competition it was difficult to distinguish between the effect of size and competition. The mixed effects models suggest that trees under high competition were less sensitive to climate than trees experiencing little competition, as only winter temperature and spring climatic water balance were significant predictors of growth for trees under high competition and the effect was slightly weaker.

Tree-ring chronologies contain low frequency variation in growth determined by endogenous tree factors (i.e. size, age, competition) that can be removed by detrending the chronologies. Dendroecological studies are usually done at a local level where many trees on one plot are cored and individual chronologies are detrended and then averaged to compute a mean chronology. The mean residual chronology is then linked to the climate data resulting in one single correlation value for each of the considered variables. For this study, only one core was taken on each plot making it impossible to build mean chronologies. To circumvent this issue, we used high spatial and temporal resolution climate data to analyze growth response of beech to climate. Using climate data at lower resolutions would have been problematic, since many of the sampled trees would have received their climate data from the same pixel, regardless of differences in elevation, slope, and exposition. We calculated correlation coefficients for selected climatic variables, treating each chronology individually, taking account of inter-tree variability in the growth-climate relationship by including a random factor to the mixed effect model. The large difference in marginal and conditional R^2 of the models highlight the importance of including a random effect accounting for endogenous factors influencing growth.

6 Conclusions

We conclude that that beech in the Uholka-Shyrokyi Luh primary forest is only slightly sensitive to climate. Correlation analysis yielded generally small correlation and the variability of tree growth response to climate was high. The mixed effects models revealed tree size as the most influential predictor of growth, highlighting the importance of including endogenous growth factors such as size and/or inter-tree competition when modelling tree growth. High winter temperatures resulted in increased radial growth. Climatic water balance of the year prior to ring formation was positively correlated to growth indicating a time lag in growth response to moisture availability. The growth response to summer temperature changed from positive (for the period 1901-2009) to negative (for the period 1989-2009). Conversely, the effect of summer climatic water balance became positive for the last 2 decades suggesting that growth of beech on the study site may become increasingly limited by drought in the future.

Dendroecological studies combining individual cores at the tree level with data from forest inventories may prove a valuable tool to model forest growth dynamics. However, assessing the effect of climate on tree growth based on individual tree ring chronologies from distinct plots was difficult as individual tree growth response to climate was highly variable. More research is needed to fully understand what drives growth of beech at the eastern extent of its range. To utilize the full potential of available forest inventory data, it would be beneficial to develop consistent methodologies to link individual growth data extracted from increment cores to forest inventory data. To better understand what drives forest dynamics, further investigations should extend the methodology to include other tree species and focus on the assessment of growth response along ecological gradients.

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Annex

A1 Competitor inclusion radius selection

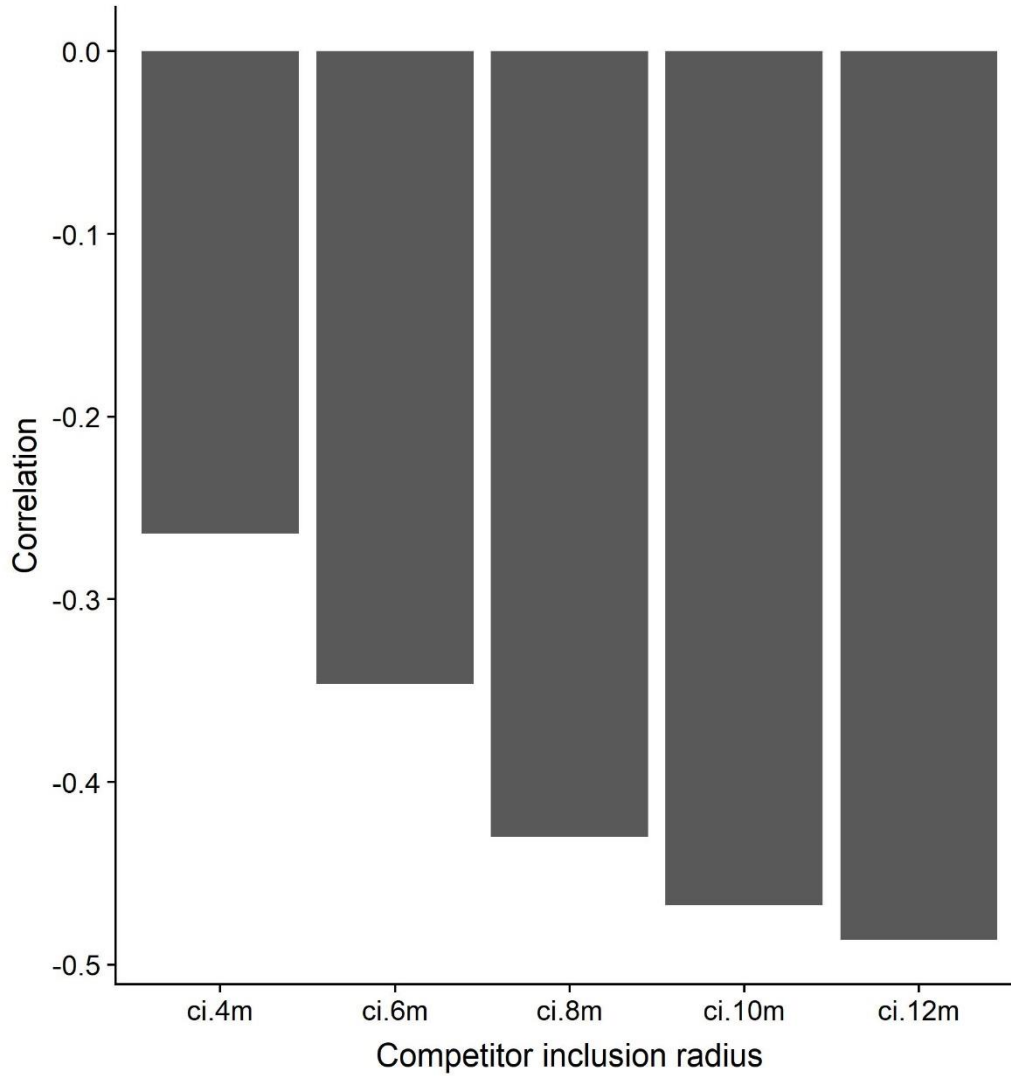


Fig. A1 Barplot showing the correlation values between mean growth (1989-2009) and the calculated competition index. Using a competitor inclusion radius of 10 returned highest correlation values and was therefore used in all further calculations.

A2 Correlogram for age, size and competition

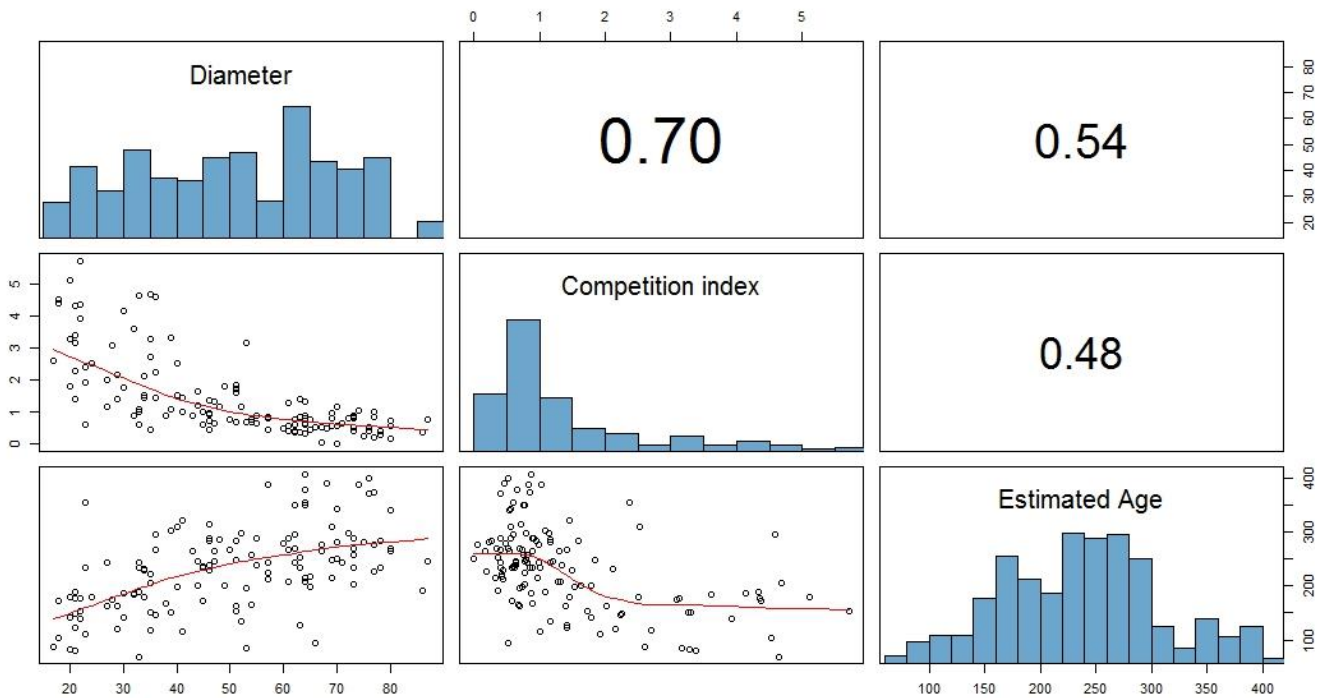


Fig. A2 correlogram of size, competition index, and estimated age at the time of coring. Diagonal line shows the histograms for Diameter, CI and estimated age. Lower graphs represent scatterplots of each variable pair. The graphs above the diagonal show the respective Pearson's correlation coefficients.

A3 R-Code

```
#####  
#### Data combination and evaluation script ####  
#####  
#### Master's thesis  
#### Author: Julian Muhmenthaler  
#### Date of last change: 26.4.2019  
rm(list=ls())  
directory <- "C://Users//julianmu//Desktop//Polybox//AAA_MASTER//Rscripts//Final Scripts"  
setwd(directory)  
  
## load libraries  
library(iki.dataclim)  
library(zyp)  
library(cowplot)  
library(reshape2)  
library(ggpubr)  
library(dplyr)  
library(tibble)  
library(SPEI)  
library(Hmisc)  
library(ggplot2)  
library(rmarkdown)  
  
#### Tree data ####  
#complete tree dataset  
tree.data.df = read.csv2("Dendro_249.csv", sep=";", dec=",")  
tree.data.df$index<- NULL  
tree.data.df$ID <- tree.data.df$name  
tree.data.df$bark[is.na(tree.data.df$bark)] <- 0  
tree.data.df$bark <- tree.data.df$bark/100  
#repeat each line 114 (1901:2009) times to make same size matrix  
tree.data.df <- tree.data.df[rep(seq_len(nrow(tree.data.df)), each=109),]  
#add a year column repeating from 1901 to 2009 for each tree  
tree.data.df$Year <- rep(c(1901:2009), times = 249)  
  
#remove unnecessary columns  
tree.data.df$name <- NULL  
tree.data.df$Index <- NULL  
tree.data.df$d7 <- NULL  
tree.data.df$x_cord <- NULL  
tree.data.df$y_cord <- NULL  
tree.data.df$crossdating1900 <- NULL  
tree.data.df$reliable_fq <- NULL  
tree.data.df$gebiet <- NULL  
tree.data.df$kronena <- NULL  
tree.data.df$hoehe <- NULL  
tree.data.df$volderba <- NULL  
  
#adjust data formats  
tree.data.df$bhd <- as.numeric(tree.data.df$bhd)  
tree.data.df$bark <- as.numeric(tree.data.df$bark)  
tree.data.df$hoehemeer <- as.numeric(tree.data.df$hoehemeer)  
  
#### Growth data ####  
growth.data <- read.csv2("Growth_data.csv", sep=";", dec=",")  
growth.data[1] <- NULL  
# attach growth values  
full.data <- left_join(tree.data.df, growth.data, by=c("ID", "Year"))
```

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```
#### Yearringage and act DBH ####
full.data$Year <- as.integer(as.character(full.data$Year))

# add year-ring-age column
full.data$yearringage <- ifelse(is.na(full.data$altercor), NA, (full.data$altercor + full.data$Year - 2009))

# add actual diameter column
act.dim.out <- data.frame()
for (i in unique(full.data$ID)){
  tmp.sub <- subset(full.data, ID == i)
  for (j in 1:(nrow(tmp.sub)-1)){
    tmp.sub$sact.dbh[j] <- ifelse(is.na(tmp.sub$YRG[j]), NA,
      tmp.sub$bhd[1]-(2*tmp.sub$bark[1]/10) - sum(tmp.sub$YRG[(1+j):109],na.rm=TRUE)/10*2)
    ##### divide by 10 to get cm, multiply by 2 to get diameter
  }
  tmp.sub$sact.dbh[109] <- tmp.sub$bhd[1]-tmp.sub$bark[1]*2/10
  act.dim.out <- rbind(act.dim.out, tmp.sub)
}
full.data <- act.dim.out
full.data$sact.dbh[full.data$sact.dbh < 0] <- NA

#### Competition data ####
comp.df <- read.csv2("Full_competition_Data.csv")
comp.df[1] <- NULL
comp.df$comp.value.10m <- comp.df$ci.10m
comp.df <- comp.df[c("plotNr", "comp.value.10m", "ci.12m")]
# attach comp data to full data.frame
full.data <- left_join(full.data, comp.df, by=c("plotNr"))

#### Climate data ####
full.data$Year <- as.integer(as.character(full.data$Year))
# Load data
clim.df <- read.csv2("Climate_Data.csv", sep=";", dec=".")
clim.df$X <- NULL
#reduce climate data frame to 249 trees in dendro 249
clim.out <- data.frame()
for (i in unique(full.data$ID)){
  clim.out <- rbind(clim.out, clim.df[clim.df$ID ==i,])
}
clim.df <- clim.out

# Make three separate data sets for Prec, Tmin, Tmax
prec.clim <- cbind(clim.df[grepl("prec_",names(clim.df))], ID = as.character(clim.df$ID))
tmin.clim <- cbind(clim.df[grepl("tmin_",names(clim.df))], ID = as.character(clim.df$ID))
tmax.clim <- cbind(clim.df[grepl("tmax_", names(clim.df))], ID = as.character(clim.df$ID))
# bring this to acceptable shape (12 cols for each of the variables)
# For Precip
prec.out <- data.frame(Year= integer(0), Jan=numeric(0), Feb=numeric(0), Mar=numeric(0), Apr=numeric(0), May=numeric(0),
  Jun=numeric(0), Jul=numeric(0),Aug=numeric(0), Sep=numeric(0), Oct=numeric(0), Nov=numeric(0), Dez=numeric(0))
for (i in 1901:2009){
  temp <- prec.clim[grepl(pattern= i , x = colnames(prec.clim))]
  temp$Year <- i
  temp$ID <- prec.clim$ID
  colnames(temp) <-c("Jan_prec","Feb_prec","Mar_prec","Apr_prec","May_prec","Jun_prec","Jul_prec","Aug_prec",
    "Sept_prec","Okt_prec","Nov_prec","Dez_prec", "Year", "ID")
  prec.out <- rbind(prec.out, temp)
}
#prev years
out.table <- data.frame()
for (i in unique(prec.out$ID)) {
  subs <- subset(prec.out, ID == i)
```

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```
for (j in colnames(subs[1:12])){
  subs[paste("prev", j, sep="_")] <- c(NA, subs[j][1:108,])
}
out.table<- rbind(out.table, subs)
}
prec.new <- out.table

#### For Tmin
tmin.out <- data.frame(Year= integer(0), Jan=numeric(0), Feb=numeric(0), Mar=numeric(0), Apr=numeric(0), May=numeric(0),
Jun=numeric(0), Jul=numeric(0), Aug=numeric(0), Sep=numeric(0), Oct=numeric(0), Nov=numeric(0), Dez=numeric(0))
for (i in 1901:2009){
  temp <- tmin.clim[grepl(pattern= i , x = colnames(tmin.clim))]/10
  temp$Year <- i
  temp$ID <- tmin.clim$ID
  colnames(temp) <-c("Jan_tmin", "Feb_tmin", "Mar_tmin", "Apr_tmin", "May_tmin", "Jun_tmin", "Jul_tmin", "Aug_tmin",
    "Sept_tmin", "Okt_tmin", "Nov_tmin", "Dez_tmin", "Year", "ID")
  tmin.out <- rbind(tmin.out, temp)
}
#prev years
out.table <- data.frame()
for (i in unique(tmin.out$ID)) {
  subs <- subset(tmin.out, ID == i)
  for (j in colnames(subs[1:12])){
    subs[paste("prev", j, sep="_")] <- c(NA, subs[j][1:108,])
  }
  out.table<- rbind(out.table, subs)
}
tmin.new <- out.table

#### For Tmax
tmax.out <- data.frame(Year= integer(0), Jan=numeric(0), Feb=numeric(0), Mar=numeric(0), Apr=numeric(0), May=numeric(0),
Jun=numeric(0), Jul=numeric(0), Aug=numeric(0), Sep=numeric(0), Oct=numeric(0), Nov=numeric(0), Dez=numeric(0))
for (i in 1901:2009){
  temp <- tmax.clim[grepl(pattern= i , x = colnames(tmax.clim))]/10
  temp$Year <- i
  temp$ID <- tmax.clim$ID
  colnames(temp)
  c("Jan_tmax", "Feb_tmax", "Mar_tmax", "Apr_tmax", "May_tmax", "Jun_tmax", "Jul_tmax", "Aug_tmax", "Sept_tmax", "Okt_tmax",
    "Nov_tmax", "Dez_tmax", "Year", "ID")
  tmax.out <- rbind(tmax.out, temp)
}
#prev years
out.table <- data.frame()
for (i in unique(tmax.out$ID)) {
  subs <- subset(tmax.out, ID == i)
  for (j in colnames(subs[1:12])){
    subs[paste("prev", j, sep="_")] <- c(NA, subs[j][1:108,])
  }
  out.table<- rbind(out.table, subs)
}
tmax.new <- out.table

#### attach climate data
full.data <- left_join(full.data, prec.new , by=c("ID", "Year"))
full.data <- left_join(full.data, tmin.new , by=c("ID", "Year"))
full.data <- left_join(full.data, tmax.new , by=c("ID", "Year"))

#### Make Long Dataset ###
# REORDER climate variables to have one column with month (reduces amount of columns)
temp2.df <- setNames(data.frame(matrix(ncol = 9, nrow = 0)), c("Prec", "prev_Prec", "Tmin", "prev_Tmin", "Tmax", "prev_Tmax", "Year", "ID",
"m.id"))
```

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```
for (i in unique(full.data$ID)){
  tmp.sub <- subset(full.data, ID == i)
  tmp.out <- setNames(data.frame(matrix(ncol = 8, nrow = 0)), c("Prec", "prev_Prec", "Tmin", "prev_Tmin", "Tmax", "prev_Tmax", "Year", "ID"))
  for (j in c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sept", "Okt", "Nov", "Dez")){
    tmp <- tmp.sub[grepl(j, names(tmp.sub))]
    tmp$Year <- tmp.sub$Year
    tmp$ID <- tmp.sub$ID
    tmp.out <- rbind(tmp.out, setNames(tmp, names(tmp.out)))
  }
  tmp.out$m.id <- rep(1:12, each= 109)
  temp2.df <- rbind(temp2.df, setNames(tmp.out, names(temp2.df)))
}
# remove climatic variables (will be added from temp2.df)
temp <- full.data[-(27:98)]
# duplicating all rows * 12 (to get monthly format)
full.data.long <- temp[rep(rownames(temp), each = 12),]
# add month column
full.data.long$m.id <- rep(1:12)
### Join together
full.data.long <- left_join(full.data.long, temp2.df, by=c("Year", "m.id", "ID"))

##### Climatic Water Balance #####
# import latitude data
lat.data <- read.csv2("Dendro_all_WGScoord.csv")
lat.data$Y_coord_wgs <- as.numeric(as.character(lat.data$Y_coord_wgs))
# join together
full.data.long <- left_join(full.data.long, lat.data[,c("Y_coord_wgs", "ID")], by = "ID")
#### Evapotranspiration
temp2 <- full.data.long
tmp <- data.frame()
for(i in unique(temp2$ID)){
  subs <- subset(temp2, ID == i)
  # calculate ETO using hargreaves function
  harg.tmp <- as.vector(hargreaves(Tmin = subs$Tmin, Pre=subs$Prec, Tmax = subs$Tmax, lat = subs$Y_coord_wgs[1]))
  subs$Harg <- harg.tmp
  subs$CWB <- subs$Prec - subs$Harg
  subs$Harg <- NULL
  out.tmp <- subs
  tmp <- rbind(tmp, out.tmp)
}
#prev years (CWB)
out.table <- data.frame()
for (i in unique(tmp$ID)) {
  subs <- subset(tmp, ID == i)
  vect <- subs["CWB"]
  vect <- c(rep(NA, times=12), vect[1:(nrow(vect)-12),])
  vect <- setNames(as.data.frame(vect), paste0("prev_", "CWB"))
  subs <- cbind(subs, vect)
  out.table <- rbind(out.table, subs)
}
full.data.long <- out.table
full.data.long$Y_coord_wgs <- NULL
#### translate back to wide format
#subset to CWB
subs <- full.data.long[c("ID", "Year", "m.id", "CWB", "prev_CWB")]
split.tmp <- split(subs, unique(subs$m.id))
## CWB
tmp <- data.frame(matrix(ncol=0, nrow=27141))
tmp <- cbind(tmp, split.tmp$`1`$ID)
tmp <- cbind(tmp, split.tmp$`1`$Year)
for (i in 1:12){
```


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```
tmp <- cbind(tmp, split.tmp[[i]]$CWB)}
colnames(tmp) <- c("ID", "Year", paste(c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sept", "Okt", "Nov", "Dez"), "CWB", sep="_"))
# join together
full.data.wide <- left_join(full.data, tmp, by=c("ID", "Year"))
## prev_CWB
tmp = data.frame(matrix(ncol=0, nrow=27141))
for (i in 1:12){
  tmp <- cbind(tmp, split.tmp[[i]]$prev_CWB)
}
tmp <- cbind(split.tmp[[1]]$ID, split.tmp[[1]]$Year, tmp)
colnames(tmp) <- c("ID", "Year", paste("prev", paste(c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sept", "Okt", "Nov", "Dez"), "CWB",
sep="_"), sep="_"))
# join
full.data.wide <- left_join(full.data.wide, tmp, by=c("ID", "Year"))

##### select output format #####
full.data <- full.data.long
full.data <- full.data.wide

##### Select only reliably dated years #####
# loop for all ID's, making temp dataframe with only reliably dated data,
temp.df <- data.frame()
for(i in unique(full.data$ID)){
  subs <- subset(full.data, ID == i)
  subs <- subset(subs, Year >= subs$dated[1])
  temp.df <- rbind(temp.df, subs)
}
full.data <- temp.df

#### Seasonal Climate (Tmax & CWB) ####
full.data$prev_summtmax <- (full.data$prev_Jun_tmax + full.data$prev_Jul_tmax + full.data$prev_Aug_tmax)/3
full.data$wintertmax <- (full.data$prev_Dez_tmax + full.data$Jan_tmax + full.data$Feb_tmax)/3
full.data$springtmax <- (full.data$prev_Mar_tmax + full.data$Apr_tmax + full.data$May_tmax)/3
full.data$summtmax <- (full.data$Jun_tmax + full.data$Jul_tmax + full.data$Aug_tmax)/3
full.data$vegpertmax <- (full.data$Apr_tmax + full.data$May_tmax + full.data$Jun_tmax + full.data$Jul_tmax + full.data$Aug_tmax +
  full.data$Sept_tmax)/6
full.data$prev_summCWB <- (full.data$prev_Jun_CWB + full.data$prev_Jul_CWB + full.data$prev_Aug_CWB)
full.data$winterCWB <- (full.data$prev_Dez_CWB + full.data$Jan_CWB + full.data$Feb_CWB)
full.data$springCWB <- (full.data$prev_Mar_CWB + full.data$Apr_CWB + full.data$May_CWB)
full.data$summCWB <- (full.data$Jun_CWB + full.data$Jul_CWB + full.data$Aug_CWB)
full.data$vegperCWB <- (full.data$Apr_CWB + full.data$May_CWB + full.data$Jun_CWB + full.data$Jul_CWB + full.data$Aug_CWB +
  full.data$Sept_CWB)

##### WRITE TO FILE #####
write.csv2(full.data, "Master_Data_Long.csv")
write.csv2(full.data, "Master_Data_Wide.csv")
```

Annex

DATA ANALYSIS

Import data

```
data.l <- read.csv2("Master_Data_Long.csv", sep=";", dec=",")
data.w <- read.csv2("Master_Data_Wide.csv", sep=";", dec=",")
data.l[1] <- NULL
data.w[1] <- NULL
# divide BAI values by 100 to get cm2
data.l$BAI <- data.l$BAI/100
data.w$BAI <- data.w$BAI/100
```

Fig. 3: Walter Lieth Climate Diagram

```
subs <- subset(data.l, Year >=1981)
subs.low <- subset(subs, hoehemeer <= 600)
subs.high <- subset(subs, hoehemeer >= 1200)
### <600m
data.WL <- matrix(nrow=4, ncol=12)
for (i in 1:12){
  tmp <- subset(subs.low, m.id == i)
  data.WL[,i] <- c(mean(tmp$TPrec), mean(tmp$Tmax), mean(tmp$Tmin), min(tmp$Tmin))
}
plotWalterLieth(data.WL, station="", alt= "< 600", per= "1981:2010", margin=c(4, 4, 5, 4),
  pcol="#005ac8", tcol="#e81800", pfcoll="#79e6e8", sfcoll=
  "#09a0d1", shem=FALSE)
### >1200m
for (i in 1:12){
  tmp <- subset(subs.high, m.id == i)
  data.WL[,i] <- c(mean(tmp$TPrec), mean(tmp$Tmax), mean(tmp$Tmin), min(tmp$Tmin))
}
plot2 <- plotWalterLieth(data.WL, station="", alt= "> 1200", per= "1981:2010", margin=c(4, 4, 5, 4),
  pcol="#005ac8", tcol="#e81800", pfcoll="#79e6e8", sfcoll=
  "#09a0d1", shem=FALSE)
```

Fig. 6: Climate trends

```
# yearly values
data.w$yprec <- data.w$Jan_prec + data.w$Feb_prec + data.w$Mar_prec + data.w$Apr_prec + data.w$May_prec + data.w$Jun_prec +
data.w$Jul_prec + data.w$Aug_prec + data.w$Sept_prec + data.w$Okt_prec + data.w$Nov_prec + data.w$Dez_prec
data.w$MyTmax <- (data.w$Jan_tmax + data.w$Feb_tmax + data.w$Mar_tmax + data.w$Apr_tmax + data.w$May_tmax + data.w$Jun_tmax +
data.w$Jul_tmax + data.w$Aug_tmax + data.w$Sept_tmax + data.w$Okt_tmax + data.w$Nov_tmax + data.w$Dez_tmax) /12
data.w$MyCWB <- data.w$Jan_CWB + data.w$Feb_CWB + data.w$Mar_CWB + data.w$Apr_CWB + data.w$May_CWB + data.w$Jun_CWB
+ data.w$Jul_CWB + data.w$Aug_CWB + data.w$Sept_CWB + data.w$Okt_CWB + data.w$Nov_CWB + data.w$Dez_CWB
```

```
# B: Yearly-Prec #
```

```
test <- data.w %>%
  group_by(Year) %>% dplyr::summarise(ID=ID[1], MyPrec=mean(yprec, na.rm=TRUE))
```

```
## significance
```

```
#1901 -2009
```

```
sign.l1 <- data.frame(zyp.trend.vector(test$MyPrec)) #not significant
```

```
#1981-2009
```

```
subs <- subset(test, Year >= 1981)
```

```
sign.s1 <- data.frame(zyp.trend.vector(subs$MyPrec))
```

```
#plot
```

```
plot1 <- ggplot() +
  geom_line(data=test, aes(x=Year, y=MyPrec), size = 1) +
  geom_segment(aes(x = 1901, y = sign.l1[11,], xend = 2009, yend = sign.l1[11,] + 109*sign.l1[2,]), color="orange", lwd=1.5) +
  geom_segment(aes(x = 1981, y = sign.s1[11,], xend = 2009, yend = sign.s1[11,] + 29*sign.s1[2,]), color="red", lwd=1.5) +
  ggtitle("b) Precipitation sum") +
  theme_bw() +
  scale_x_continuous( breaks = c(1900,1910,1920,1930,1940,1950,1960,1970,1980,1990,2000,2010))+
  theme(axis.title.x=element_blank()) +
  ylab("[mm]")
```

```
## A: Yearly mean Tmax ##
```

Annex

```
test <- data.w %>%
  group_by(Year) %>% dplyr::summarise(ID=ID[1], mMyTmax=mean(MyTmax, na.rm=TRUE))
## significance
#1901 -2009
sign.l2 <- data.frame(zyp.trend.vector(test$mMyTmax)) #not significant
#1981 -2009
subs <- subset(test, Year >= 1981)
sign.s2 <- data.frame(zyp.trend.vector(subs$mMyTmax))
#plot
plot2 <- ggplot(data=test) +
  geom_line(data=test, aes(x=Year, y=mMyTmax), size = 1) +
  geom_segment(aes(x = 1901, y = sign.l2[11,], xend = 2009, yend = sign.l2[11,] + 109*sign.l2[2,]), color="orange", lwd=1.5) +
  geom_segment(aes(x = 1981, y = sign.s2[11,], xend = 2009, yend = sign.s2[11,] + 29*sign.s2[2,]), color="red", lwd=1.5) +
  ggtitle("a) Mean maximum temperature") +
  theme_bw() +
  scale_x_continuous(breaks = c(1900,1910,1920,1930,1940,1950,1960,1970,1980,1990,2000,2010))+
  theme(axis.title.x=element_blank())+
  ylab("[°C]")

### C: CWB
test <- data.w %>%
  group_by(Year) %>% dplyr::summarise(ID=ID[1], MyCWB=mean(MyCWB, na.rm=TRUE))
#1901-2009
sign.l3 <- data.frame(zyp.trend.vector(test$MyCWB)) #not significant
#1981 -2009
subs <- subset(test, Year >= 1981)
sign.s3 <- data.frame(zyp.trend.vector(subs$MyCWB))
#plot
plot3 <- ggplot(data=test) +
  geom_line(aes(x=Year, y=MyCWB), size = 1) +
  geom_segment(aes(x = 1901, y = sign.l3[11,], xend = 2009, yend = sign.l3[11,] + 109* sign.l3[2,]), color="orange", lwd=1.5) +
  geom_segment(aes(x = 1981, y = sign.s3[11,], xend = 2009, yend = sign.s3[11,] + 29*sign.s3[2,]), color="red", lwd=1.5) +
  ggtitle("c) Climatic water balance") +
  theme_bw() +
  scale_x_continuous(breaks = c(1900,1910,1920,1930,1940,1950,1960,1970,1980,1990,2000,2010))+
  theme(axis.title.x =element_blank()) +
  ylab("[mm]")

### Plot all three in one graph
cowplot::plot_grid(plot2, plot1, plot3, ncol = 1, align = "v", rel_heights = c(1,1,1.1))
ggsave("Clim_trends.pdf", width = 18, height=16, units=c("cm"), dpi=300,
path="C://Users//Julian//Desktop//Polybox//AAA_MASTER//Manuscript//Bilder//Materials")

##### GROWTH TRENDS #####
#### FIG 6: Time trend ####
#group by year and summarize
subs <- data.w %>% group_by(Year) %>% dplyr::summarize(samp.depth=n(), sdYRG=sd(YRG, na.rm=T), mYRG=mean(YRG, na.rm=T),
sdBAI=sd(BAI, na.rm=T), mBAI=mean(BAI, na.rm=T))

## Tree ring width
# significance
# 1901-2009
tmp.l1 <- data.frame(zyp.trend.vector(subs$mYRG))
# 1981-2009
tmp.s1 <- data.frame(zyp.trend.vector(subset(subs, Year >= 1981)$mYRG))
# plot
plot1 <- ggplot(data=subs, aes(x=Year, y=mYRG)) +
  geom_line() +
  geom_ribbon(aes(ymin=mYRG-sdYRG/sqrt(samp.depth), ymax=mYRG+sdYRG/sqrt(samp.depth)), linetype=2, fill="blue", alpha=0.4) +
  geom_area(aes(y=samp.depth/100), alpha=0.1) +
  scale_y_continuous(sec.axis = sec_axis(~ . * 100, name = "Sample Depth")) +
  labs(x = "Year")+
  geom_segment(aes(x = 1900, y = tmp.l1[11,], xend = 2009, yend = tmp.l1[11,] + 108*tmp.l1[2,]), color="orange", lwd=1.5) +
```

Annex

```
geom_segment(aes(x = 1981, y = tmp.s1[11,], xend = 2009, yend = tmp.s1[11,] + 29*tmp.s1[2,]), color="red", lwd=1.5) +
ylab("Mean tree-ring width [mm]") +
theme_bw()+
scale_x_continuous(breaks=seq(from=1900, to=2010, by=10), minor_breaks = seq(from=1900, to=2010, by=5)) +
theme(axis.title.x = element_blank()+
coord_cartesian(ylim = c(0, 2.5), xlim =c(1900,2010))

##BAI
#significance
# 1901-2009
tmp.l2 <- data.frame(zyp.trend.vector(subs$mBAI))
tmp.s2 <- data.frame(zyp.trend.vector(subset(subs, Year >= 1981)$mBAI))

plot2 <- ggplot(data=subs, aes(x=Year, y=mBAI)) +
  geom_line() +
  geom_ribbon(aes(ymin=mBAI-sdBAI/sqrt(samp.depth), ymax=mBAI+sdBAI/sqrt(samp.depth)), linetype=2, fill="blue", alpha=0.4) +
  geom_area(aes(y=samp.depth*0.14), alpha=0.1) +
  scale_y_continuous(sec.axis = sec_axis(~ . /0.14 , name = "Sample Depth")) +
  labs(x = "Year")+
  geom_segment(aes(x = 1900, y = tmp.l2[11,], xend = 2009, yend = tmp.l2[11,] + 108*tmp.l2[2,]), color="orange", lwd=1.5) +
  geom_segment(aes(x = 1981, y = tmp.s2[11,], xend = 2009, yend = tmp.s2[11,] + 29*tmp.s2[2,]), color="red", lwd=1.5) +
  ylab(expression(paste("Mean basal area increment ", paste("[cm]^2", "]")))) +
  theme_bw()+
  scale_x_continuous(breaks=seq(from=1900, to=2010, by=10), minor_breaks = seq(from=1900, to=2010, by=5)) +
  coord_cartesian(ylim = c(0, 35), xlim =c(1900,2010))

#plot together
cowplot::plot_grid(plot1, plot2, ncol=1, align="v", rel_heights = c(1,1.1))
#save graphic
ggsave("BAI_YRG_Growthtrend_by_Year.pdf", width = 20, height= 16, units="cm", dpi=300,
  path="C://Users//Julian//Desktop//Polybox//AAA_MASTER//Manuscript//Bilder//Materials")

#### Fig 7: cambial age ####
# grouped by year-ring age
subs <- data.w %>% group_by(yearringage) %>% dplyr::summarize(samp.depth=n(), sdYRG=sd(YRG, na.rm=T), mYRG=mean(YRG, na.rm=T),
  sdBAI=sd(BAI, na.rm=T), mBAI=mean(BAI, na.rm=T))

## 7.A: Tree ring width
# significance
tmp.3 <- data.frame(zyp.trend.vector(subs$mYRG))
#plot
plot3 <- ggplot(data=subs, aes(x=yearringage, y=mYRG)) +
  geom_line() +
  geom_ribbon(aes(ymin=mYRG-sdYRG/sqrt(samp.depth), ymax=mYRG+sdYRG/sqrt(samp.depth)), linetype=2, fill="blue", alpha=0.4) +
  geom_area(aes(y=samp.depth/30), alpha=0.1) +
  labs(y = "Mean tree-ring width [mm]") +
  geom_abline(intercept = tmp.3[11,], slope=tmp.3[2,], color="orange", lwd=1.5) +
  theme_bw()+
  scale_x_continuous(breaks=seq(from=0, to=450, by=50)) +
  scale_y_continuous(limits=c(0,3), sec.axis = sec_axis(~ . * 30 , name = "Sample Depth")) +
  theme(axis.title.x = element_blank()+
  coord_cartesian(ylim = c(0, 3), xlim =c(0,400))

## 7.B: BAI
#significance
tmp.4 <- data.frame(zyp.trend.vector(subs$mBAI))
#plot
plot4 <- ggplot(data=subs, aes(x=yearringage,y=mBAI)) +
  geom_line() +
  geom_ribbon(aes(ymin=mBAI-sdBAI/sqrt(samp.depth), ymax=mBAI+sdBAI/sqrt(samp.depth)), linetype=2, fill="blue", alpha=0.4) +
```

Annex

```
geom_area(aes(y=samp.depth*0.65, alpha=0.1) +
scale_y_continuous(limits=c(0,60), sec.axis = sec_axis(~ . /0.65 , name = "Sample Depth")) +
labs(x = "Year-ring age [y]")+
geom_abline(intercept = tmp.4[1,], slope=tmp.4[2,], color="orange", lwd=1.5) +
ylab(expression(paste("Mean basal area increment ", paste("[cm"^^2", "]")))) +
theme_bw()+
scale_x_continuous(breaks=seq(from=0, to=450, by=50)) +
coord_cartesian(ylim = c(0, 60), xlim =c(0,400))
# plot together
cowplot::plot_grid(plot3, plot4, ncol=1, align="v", rel_heights = c(1,1.1))
ggsave("BAI_YRG_GrowthTrend_YEARRINGAGE.pdf", width = 18, height=16, units="cm", dpi=300,
path="C://Users//julianmu//Desktop//Polybox//AAA_MASTER//Manuscript//Bilder//Materials")

### % trees showing significant increase in growth
# Tree ring width
g.trends <- data.frame()
for (i in unique(data.w$ID)){
  temp <- subset(data.w, ID==i)
  trend <- data.frame(zyp.trend.vector(temp$YRG))
  trend <- cbind(temp$ID[1],trend[2,],trend[6,])
  g.trends<- rbind(g.trends, trend)
}
# select significant p<0.05
sign.df <- g.trends[g.trends$V3 < 0.05,]
nonsign.df <- g.trends[g.trends$V3 > 0.05,]
sign.pos <- sign.df[sign.df$V2 > 0,]
sign.neg <- sign.df[sign.df$V2 < 0,]
# % positive
nrow(sign.pos)/nrow(g.trends)
# % non-significant
nrow(nonsign.df)/nrow(g.trends)
# % negative
nrow(sign.neg)/nrow(g.trends)

### BAI
g.trends <- data.frame()
for (i in unique(data.w$ID)){
  temp <- subset(data.w, ID==i)
  trend <- data.frame(zyp.trend.vector(temp$BAI))
  trend <- cbind(temp$ID[1],trend[2,],trend[6,])
  g.trends<- rbind(g.trends, trend)
}
### select significant p<0.05
sign.df <- g.trends[g.trends$V3 < 0.05,]
nonsign.df <- g.trends[g.trends$V3 > 0.05,]
sign.pos <- sign.df[sign.df$V2 > 0,]
sign.neg <- sign.df[sign.df$V2 < 0,]
# % positive
nrow(sign.pos)/nrow(g.trends)
# % non-significant
nrow(nonsign.df)/nrow(g.trends)
# % negative
nrow(sign.neg)/nrow(g.trends)

#### Fig 10: Competition classes ####
# subset to data with reasonable competition values (removes 5 trees: P63B1, P173B8, P237B9, P334B9, P276B1)
subs <- subset(data.w, comp.value.10m<6)
subs <- subs[subs$ID != "P64B8",] # remove one outlier
# only looking at timespan where competition is assumed as +/- cst
subs <- subset(subs, Year >= 1989)
```

Annex

```
# summarize data by ID
CI.test <- subs %>%
  group_by(ID) %>%
  dplyr::summarize(MeanG = mean(BAI, na.rm=T), masl=hoehemeer[1], CI=comp.value.10m[1], BHD = bhd[1])
## Exponential decay model
exp.mod <- lm(log(MeanG) ~ CI, data=CI.test)
summary(exp.mod) #R2 =0.398
#### Predict Mean Growth from Model
CI.vect <- seq(from= 0,6, by=0.1)
# predict variables for curve
pred <- exp(predict(exp.mod,list(CI=CI.vect)))
pred <- as.data.frame(cbind(MeanG= pred, CI = CI.vect))
# set threshold value log(BAI/2)-intercept/slope
thresh = (log(exp(3.54640)/2)-3.54640)/(-0.51195)

#### add competition classes ####
subs$comp.class <- ifelse(subs$comp.value.10m <= thresh, "Low", "High")
data.w$comp.class <- ifelse(data.w$comp.value.10m <= thresh, "Low", "High")
data.l$comp.class <- ifelse(data.w$comp.value.10m <= thresh, "Low", "High")
# reorder CC levels
subs$comp.class <- factor(subs$comp.class, levels=c("Low", "High"))
data.w$comp.class <- factor(data.w$comp.class, levels=c("Low", "High"))
data.l$comp.class <- factor(data.l$comp.class, levels=c("Low", "High"))
## summarize with comp classes
CI.test <- subs %>%
  group_by(ID) %>%
  dplyr::summarize(MeanG = mean(BAI, na.rm=T), masl=hoehemeer[1], CI=comp.value.10m[1], CC= comp.class[1], BHD = bhd[1])
# plot
ggplot(data=CI.test, aes(x=CI, y=MeanG)) + geom_point(aes(col=CC), size=2) +
  geom_line(data=pred, aes(x=CI, y=MeanG), color= "red", lwd=1) +
  theme_bw() +
  scale_x_continuous(breaks=seq(from=0, to=20, by=0.5)) +
  xlab("Competition Index [1]") +
  ylab(expression(paste("Mean basal area increment ", paste("[cm]^2", "]")))) +
  geom_vline(xintercept = thresh) +
  ylim(c(0,80)) +
  scale_color_manual("Competition \nClass",
    breaks = c("Low", "High"),
    labels = c("Low (n=151)", "High (n=60)"),
    values = c("#FC8D59", "#91CF60"))
ggsave("DBH_vs_CI_comp_cutoff.pdf", width = 20, height=14, units="cm", dpi=300,
  path="C:/Users/julianmu/Desktop/Polybox/AAA_MASTER/Manuscript/Bilder/Materials")

#### TREECLIM ####
library(treeclim)
library(dplR)
library(stats)

#### Seasonal correlations Fig 9 & 12:####
# run script below for (1901-2009) and (1989-2009)
#subset for the chosen timeperiod
subs <- subset(data.l, Year>= 1989)
dcc.fin.tmax <- data.frame()
dcc.fin.tmin <- data.frame()
dcc.fin.prec <- data.frame()
dcc.fin.CWB <- data.frame()
#### LOOP over all id's
for (i in unique(subs$ID)){

# Make Subset for single TreeID in loop
temp <- subset(subs, ID == i)
temp.chron <- subset(temp, m.id==1)
```

Annex

```
temp.BAI.chron <- data.frame(BAI = temp.chron$BAI)
rownames(temp.BAI.chron) <- temp.chron$Year
##### make chronology
tmp.BAI.chron <- chron(temp.BAI.chron, prewhiten=TRUE)

#### run dcc
test.tmax <- dcc(chrono= tmp.BAI.chron, climate=temp[,c("Year", "m.id", "Tmax")],
  selection = .mean(-6:-8, "Tmax") + .mean(-9:-11, "Tmax") + .mean(-12:2, "Tmax") + .mean(3:5, "Tmax") + .mean(6:8, "Tmax"),
  method="correlation")
test.tmin <- dcc(chrono= tmp.BAI.chron, climate=temp[,c("Year", "m.id", "Tmin")],
  selection = .mean(-6:-8, "Tmin") + .mean(-9:-11, "Tmin") + .mean(-12:2, "Tmin") + .mean(3:5, "Tmin") + .mean(6:8, "Tmin"),
  method="correlation")
test.prec <- dcc(chrono= tmp.BAI.chron, climate=temp[,c("Year", "m.id", "Prec")],
  selection = .sum(-6:-8, "Prec") + .sum(-9:-11, "Prec") + .sum(-12:2, "Prec") + .sum(3:5, "Prec") + .sum(6:8, "Prec"),
  method="correlation")
test.CWB <- dcc(chrono= tmp.BAI.chron, climate=temp[,c("Year", "m.id", "CWB")],
  selection = .sum(-6:-8, "CWB") + .sum(-9:-11, "CWB") + .sum(-12:2, "CWB") + .sum(3:5, "CWB") + .sum(6:8, "CWB"),
  method="correlation")

#### fill output table
dcc.fin.tmax <- rbind(dcc.fin.tmax, test.tmax$coef$coef)
dcc.fin.tmin <- rbind(dcc.fin.tmin, test.tmin$coef$coef)
dcc.fin.prec <- rbind(dcc.fin.prec, test.prec$coef$coef)
dcc.fin.CWB <- rbind(dcc.fin.CWB, test.CWB$coef$coef)
}

### rename output tables
dcc.fin.tmax <- setNames(dcc.fin.tmax, paste0("tmax", c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8")))
dcc.fin.tmax$ID <- unique(subs$ID)
dcc.fin.tmin <- setNames(dcc.fin.tmin, paste0("tmin", c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8")))
dcc.fin.tmin$ID <- unique(subs$ID)
dcc.fin.prec <- setNames(dcc.fin.prec, paste0("prec",c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8")))
dcc.fin.prec$ID <- unique(subs$ID)
dcc.fin.CWB <- setNames(dcc.fin.CWB, paste0("CWB",c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8")))
dcc.fin.CWB$ID <- unique(subs$ID)

### join aggregated values for each tree to the full.df
temp <- subset(data.l, Year==2009)
temp <- subset(temp, m.id==1)
tmp <- left_join(temp, dcc.fin.tmax, by = "ID")
tmp <- left_join(tmp, dcc.fin.tmin, by = "ID")
tmp <- left_join(tmp, dcc.fin.prec, by = "ID")
tmp <- left_join(tmp, dcc.fin.CWB, by = "ID")

# melt for more efficient plotting
dcc.coeff.df <- melt(tmp, id.vars= c("ID", "act.dbh", "hoehemeer", "comp.value.10m", "comp.class"),
  measure.vars=c(paste0("tmax", c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8")),
  paste0("tmin", c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8")),
  paste0("prec",c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8")),
  paste0("CWB",c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8"))))

### individual data frames
dcc.coeff.tmax <- melt(tmp, id.vars= c("ID", "act.dbh", "hoehemeer", "comp.value.10m", "comp.class"),
  measure.vars=c(paste0("tmax", c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8"))))
dcc.coeff.tmin <- melt(tmp, id.vars= c("ID", "act.dbh", "hoehemeer", "comp.value.10m", "comp.class"),
  measure.vars=c(paste0("tmin", c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8"))))
dcc.coeff.prec <- melt(tmp, id.vars= c("ID", "act.dbh", "hoehemeer", "comp.value.10m", "comp.class"),
  measure.vars=c(paste0("prec",c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8"))))
dcc.coeff.CWB <- melt(tmp, id.vars= c("ID", "act.dbh", "hoehemeer", "comp.value.10m", "comp.class"),
  measure.vars=c(paste0("CWB",c("-6:-8", "-9:-11", "-12:2", "3:5", "6:8"))))

#vector for labelling x-axis
label.vect <- c("p.Summer", "p.Fall", "Winter", "Spring", "Summer")
```

Fig 9: seasonal correlations (1901-2009)

```

plot1 <- ggplot(data=dcc.coeff.tmax, aes(x=variable, y =value)) +
  geom_boxplot(fill='#A4A4A4') +
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  ggtitle("a) Maximum temperature") +
  theme_bw()+
  theme(axis.title.x=element_blank(),
        axis.ticks.x=element_blank(),
        axis.text.x =element_blank(),
        axis.ticks.y=element_blank(),
        axis.title.y=element_blank())+
  ylim(-0.4,0.4)

plot2 <- ggplot(data=dcc.coeff.tmin, aes(x=variable, y =value)) +
  geom_boxplot(fill='#A4A4A4') +
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  theme_bw()+
  ggtitle("b) Minimum temperature")+
  theme(axis.title.x=element_blank(),
        axis.ticks.x=element_blank(),
        axis.text.x =element_blank(),
        axis.text.y =element_blank(),
        axis.title.y=element_blank(),
        axis.ticks.y=element_blank()) +
  ylim(-0.4,0.4)

plot3 <- ggplot(data=dcc.coeff.prec, aes(x=variable, y =value)) +
  geom_boxplot(fill='#A4A4A4') +
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  theme_bw()+
  ggtitle("c) Precipitation")+
  theme(legend.position = "none",
        axis.title.y=element_blank())+
  xlab("Season")+
  ylim(-0.4,0.4)

plot4 <- ggplot(data=dcc.coeff.CWB, aes(x=variable, y =value)) +
  geom_boxplot(fill='#A4A4A4') +
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  theme_bw()+
  ggtitle("d) Climatic water balance")+
  theme(axis.text.y=element_blank(),
        axis.ticks.y=element_blank(),
        axis.title.y=element_blank())+
  theme(legend.position = "none")+
  xlab("Season")+
  ylim(-0.4,0.4)
ggarrange(plot1, plot2, plot3, plot4, ncol=2, nrow=2, heights=c(1,1.1), common.legend = TRUE, legend="right")
ggsave("Dcc_seasonal_long.jpeg", width = 18, height = 14, units="cm", dpi=300,
       path="C:/Users/julianmu//Desktop//Polybox//AAA_MASTER//Manuscript//Bilder//Materials")

```

Fig.12 Seasonal correlations with competiton classes (1989-2009)

```

label.vect <- c("p.Summer", "p.Fall", "Winter", "Spring", "Summer")
plot1 <- ggplot(data=dcc.coeff.tmax, aes(x=variable, y =value, fill=comp.class, alpha=0.7)) +
  geom_boxplot() +
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +

```


Annex

```
ggtitle("a) Maximum temperature") +
theme_bw()+
theme(axis.title.x=element_blank(),
      axis.ticks.x=element_blank(),
      axis.text.x =element_blank(),
      axis.ticks.y=element_blank(),
      axis.title.y=element_blank(),
      legend.position="none")+
ylim(-0.6,0.6)+
scale_fill_manual("Competition \nClass",
                 breaks = c("Low", "High"),
                 values = c("#91CF60", "#FC8D59"))
```

```
plot2 <- ggplot(data=dcc.coeff.tmin, aes(x=variable, y =value, fill=comp.class, alpha=0.7)) +
  geom_boxplot() +
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  ggtitle("b) Minimum temperature")+
  theme_bw()+
  theme(axis.title.x=element_blank(),
        axis.ticks.x=element_blank(),
        axis.text.x =element_blank(),
        axis.text.y =element_blank(),
        axis.title.y=element_blank(),
        axis.ticks.y=element_blank(),
        legend.position = "none") +
  ylim(-0.6,0.6)+
  scale_fill_manual("Competition \nClass",
                   breaks = c("Low", "High"),
                   values = c("#91CF60", "#FC8D59"))
```

```
plot3 <- ggplot(data=dcc.coeff.prec, aes(x=variable, y =value, fill=comp.class, alpha=0.7)) +
  geom_boxplot() +
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  ggtitle("c) Precipitation")+
  theme_bw()+
  theme(axis.title.y=element_blank(),legend.position="none")+
  xlab("Season")+
  ylim(-0.6,0.6)+
  scale_fill_manual("Competition \nClass",
                   breaks = c("Low", "High"),
                   values = c("#91CF60", "#FC8D59"))
```

```
plot4 <- ggplot(data=dcc.coeff.CWB, aes(x=variable, y =value, fill=comp.class, alpha=0.7)) +
  geom_boxplot() +
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  ggtitle("d) Climatic water balance")+
  theme_bw()+
  theme(axis.text.y=element_blank(),
        axis.ticks.y=element_blank(),
        axis.title.y=element_blank())+
  theme(legend.position = "none")+
  xlab("Season")+
  ylim(-0.6,0.6)+
  scale_fill_manual("Competition \nClass",
                   breaks = c("Low", "High"),
                   values = c("#91CF60", "#FC8D59"))
```

Annex

```
# plot grid
plotg <- plot_grid(plot1,plot2,plot3,plot4, ncol=2, rel_heights = c(1,1.1), rel_widths = c(1.05,1))
# get legend
plot.leg <- ggplot(data=dcc.coef.prec, aes(x=variable, y =value, fill = comp.class)) +
  geom_boxplot()+
  labs(fill = "Competition \nClass") +
  scale_fill_manual("Competition \nClass",
    breaks = c("Low", "High"),
    labels=c("Low (n = 151)", "High (n = 60)"),
    values = c("#91CF60", "#FC8D59"))
plot.leg <- get_legend(plot.leg)
# final plot
plot_grid(plotg, plot.leg, rel_widths = c(1,0.24))
#save to jpeg
ggsave("Dcc_seasonal_comp_BAI.pdf", width = 18, height = 14, units="cm", dpi=300,
  path="C://Users//julianmu//Desktop//Polybox//AAA_MASTER//Manuscript//Bilder//Materials")
```

Monthly correlations Fig. 8 & 11

```
# run script below for (1901-2009) and (1989-2009)
subs <- subset(data.l, Year>= 1989)
dcc <- data.frame(m.id = c(1:16))
dcc.fin <- data.frame()
```

LOOP over each id

```
for (i in unique(subs$ID)){
  temp <- subset(subs, ID == i)
  temp.chron <- subset(temp, m.id==1)
  temp.bai.chron <- data.frame(BAI = temp.chron$BAI)
  rownames(temp.bai.chron) <- temp.chron$Year
  ##### make chronology
  tmp.bai.chron <- chron(temp.bai.chron, prewhiten=TRUE)
```

DCC (Bootstrapped correlation values BAI-CLIM)

```
dcc.prec <- dcc(chrono = tmp.bai.chron, climate=temp[,c("Year", "m.id", "Prec")], selection = -6:9, method="correlation")
dcc.tmin <- dcc(chrono = tmp.bai.chron, climate=temp[,c("Year", "m.id", "Tmin")], selection = -6:9, method="correlation")
dcc.tmax <- dcc(chrono = tmp.bai.chron, climate=temp[,c("Year", "m.id", "Tmax")], selection = -6:9, method="correlation")
dcc.CWB <- dcc(chrono = tmp.bai.chron, climate=temp[,c("Year", "m.id", "CWB")], selection = -6:9, method="correlation")
dcc$ID <- rep(temp$ID[1], times=16)
dcc$comp.val <- rep(temp$comp.value.10m[1], times=16)
dcc$comp.class <- rep(temp$comp.class[1], times=16)
dcc$tmax.coef <- dcc.tmax$coef$coef
dcc$tmin.coef <- dcc.tmin$coef$coef
dcc$prec.coef <- dcc.prec$coef$coef
dcc$CWB <- dcc.CWB$coef$coef
#### fill output table
dcc.fin <- rbind(dcc.fin, dcc)
}
test.df <- melt(dcc.fin, id.vars=c("ID", "m.id", "comp.class", "comp.val"))
```

Fig 11: monthly correlations with competition classes (1989-2009)

```
test.df$m.id <- as.factor(test.df$m.id)
label.vect <- c("-", "J", "-", "A", "-", "S", "-", "O", "-", "N", "-", "D", "J", "F", "M", "A", "M", "J", "J", "A", "S")

subs <- subset(test.df, variable=="tmax.coef")
plot1 <- ggplot(data=subs, aes(x=m.id, y=value, fill=comp.class, alpha=0.7)) +
  geom_boxplot() +
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  ggtitle("a) Maximum temperature") +
  theme_bw()+
  theme(axis.title.x=element_blank(),
    axis.ticks.x=element_blank(),
```

Annex

```
axis.text.x =element_blank(),
axis.ticks.y=element_blank(),
axis.title.y=element_blank(),
legend.position = "none") +
scale_fill_manual("Competition \nClass",
breaks = c("Low", "High"),
values = c("#91CF60", "#FC8D59")) +
ylim(-0.6,0.6)

subs <- subset(test.df, variable=="tmin.coef")
plot2 <- ggplot(data=subs, aes(x=m.id, y =value, fill=comp.class, alpha=0.7)) +
geom_boxplot() +
scale_x_discrete(labels=label.vect) +
geom_abline(aes(slope=0, intercept=0)) +
ggtitle("b) Minimum temperature")+
theme_bw()+
theme(axis.title.x=element_blank(),
axis.ticks.x=element_blank(),
axis.text.x =element_blank(),
axis.text.y =element_blank(),
axis.title.y=element_blank(),
axis.ticks.y=element_blank(),
legend.position = "none") +
scale_fill_manual("Competition \nClass",
breaks = c("Low", "High"),
values = c("#91CF60", "#FC8D59")) +
ylim(-0.6,0.6)

subs <- subset(test.df, variable=="prec.coef")
plot3 <- ggplot(data=subs, aes(x=m.id, y =value, fill=comp.class, alpha=0.7)) +
geom_boxplot() +
theme_bw()+
scale_x_discrete(labels=label.vect) +
geom_abline(aes(slope=0, intercept=0)) +
ggtitle("c) Precipitation")+
theme(legend.position = "none",
axis.title.y=element_blank())+
xlab("Month")+
scale_fill_manual("Competition \nClass",
breaks = c("Low", "High"),
values = c("#91CF60", "#FC8D59")) +
ylim(-0.6,0.6)

subs <- subset(test.df, variable=="CWB")
plot4 <- ggplot(data=subs, aes(x=m.id, y =value, fill=comp.class, alpha=0.7)) +
geom_boxplot() +
theme_bw()+
scale_x_discrete(labels=label.vect) +
geom_abline(aes(slope=0, intercept=0)) +
ggtitle("d) Climatic water balance")+
theme(axis.text.y=element_blank(),
axis.ticks.y=element_blank(),
axis.title.y=element_blank())+
theme(legend.position = "none") +
xlab("Month")+
scale_fill_manual("Competition \nClass",
breaks = c("Low", "High"),
values = c("#91CF60", "#FC8D59")) +
ylim(-0.6,0.6)
```

Annex

```
## plot
plotg <- plot_grid(plot1,plot2,plot3,plot4, ncol=2, rel_heights = c(1,1.1))
# legend
plot.leg <- ggplot(data=subs, aes(x=m.id, y =value, fill=comp.class)) + geom_boxplot() +
  theme(axis.text.y=element_blank(),
        axis.ticks.y=element_blank(),
        axis.title.y=element_blank())+
  scale_fill_manual("Competition \nClass",
                   breaks = c("Low", "High"),
                   labels = c("Low (n=151)", "High (n=60)"),
                   values = c("#91CF60", "#FC8D59"))
plot.leg <- get_legend(plot.leg)
# final plot
plot_grid(plotg, plot.leg, rel_widths = c(1,0.28))
#save to jpeg
ggsave("dcc_monthly_comp.jpeg", width = 20, height = 14, units="cm", dpi=300,
       path="C://Users//julianmu//Desktop//Polybox//AAA_MASTER//Manuscript//Bilder//Materials")
```

Fig. 8: monthly correlations (1901-2009)

```
test.df$m.id <- as.factor(test.df$m.id)
label.vect <- c("-", "J", "-J", "-A", "-S", "-O", "-N", "-D", "J", "F", "M", "A", "M", "J", "J", "A", "S")
subs <- subset(test.df, variable=="tmax.coef")
plot1 <- ggplot(data=subs, aes(x=m.id, y =value)) +
  geom_boxplot(fill="#A4A4A4") +
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  ggtitle("a) Maximum temperature") +
  theme_bw()+
  theme(axis.title.x=element_blank(),
        axis.ticks.x=element_blank(),
        axis.text.x =element_blank(),
        axis.ticks.y=element_blank(),
        axis.title.y=element_blank(),
        legend.position = "none") +
  ylim(-0.4,0.4)
subs <- subset(test.df, variable=="tmin.coef")
plot2 <- ggplot(data=subs, aes(x=m.id, y =value)) +
  geom_boxplot(fill="#A4A4A4") +
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  ggtitle("b) Minimum temperature")+
  theme_bw()+
  theme(axis.title.x=element_blank(),
        axis.ticks.x=element_blank(),
        axis.text.x =element_blank(),
        axis.text.y =element_blank(),
        axis.title.y=element_blank(),
        axis.ticks.y=element_blank(),
        legend.position = "none") +
  ylim(-0.4,0.4)
subs <- subset(test.df, variable=="prec.coef")
plot3 <- ggplot(data=subs, aes(x=m.id, y =value)) +
  geom_boxplot(fill="#A4A4A4") +
  theme_bw()+
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  ggtitle("c) Precipitation")+
  theme(legend.position = "none",
        axis.title.y=element_blank())+
  xlab("Month")+
  scale_fill_brewer(palette="RdYlGn", direction= -1)+
  ylim(-0.4,0.4)
```

Annex

```
subs <- subset(test.df, variable=="CWB")
plot4 <- ggplot(data=subs, aes(x=m.id, y =value)) +
  geom_boxplot(fill="#A4A4A4') +
  theme_bw()+
  scale_x_discrete(labels=label.vect) +
  geom_abline(aes(slope=0, intercept=0)) +
  ggtitle("d) Climatic water balance")+
  theme(axis.text.y=element_blank(),
        axis.ticks.y=element_blank(),
        axis.title.y=element_blank())+
  theme(legend.position = "none") +
  xlab("Month")+
  scale_fill_brewer(palette="RdYlGn", direction= -1)+
  ylim(-0.4,0.4)

## plot grid
library(cowplot)
plot_grid(plot1,plot2,plot3,plot4, ncol=2, rel_heights = c(1,1.1))
## save to jpeg
ggsave("dcc_monthly.jpeg", width = 20, height = 14, units="cm", dpi=300,
       path="C:/Users/julianmu/Desktop/Polybox/AAA_MASTER/Manuscript/Bilder/Materials")

#### Mixed effects Model ####
#### Load data
library(lme4)
library(nlme)
library(MuMIn)
subs.mem <- data.w

### subset to necessary variables
mem.data <- dplyr::select(subs.mem, "ID", "Year", "BAI", "act.dbh", "comp.class",
  "prev_summCWB", "springCWB", "summCWB", "winterCWB",
  "prev_summtmax", "summtmax", "wintertmax")

### scale independent variables
mem.data$dbh.sc <- scale(mem.data$act.dbh, center=TRUE, scale= T)
mem.data$p.su.cwb <- scale(mem.data$prev_summCWB, center=TRUE, scale= T)
mem.data$sp.cwb <- scale(mem.data$springCWB, center=TRUE, scale= T)
mem.data$su.cwb <- scale(mem.data$summCWB, center=TRUE, scale= T)
mem.data$w.tmax <- scale(mem.data$wintertmax, center=TRUE, scale=T)
mem.data$p.su.tmax <- scale(mem.data$prev_summtmax, center=TRUE, scale= T)
mem.data$su.tmax <- scale(mem.data$summtmax, center=TRUE, scale= T)
mem.data$ID <- as.factor(as.character(mem.data$ID))

#### subset to observed categories
subs.long <- subset(mem.data)
subs.short <- subset(mem.data, Year >= 1989)
subs.low <- subset(subs.short, comp.class=="Low")
subs.high <- subset(subs.short, comp.class=="High")

#formula
form_s <- log(BAI) ~ dbh.sc*su.cwb + p.su.tmax + p.su.cwb + sp.cwb + w.tmax + su.tmax
```

Annex

```
#### FIND OPTIMAL RANDOM STRUCTURE (REML-comparison possible since same fixed structure)
```

```
# no random term
```

```
lm.1 <- gls(form_s,  
            data = subs.long,  
            method = "REML",  
            na.action = na.exclude)
```

```
# random intercept
```

```
lm.2 <- lme(form_s,  
            data = subs.long,  
            random = ~ 1 | ID,  
            method = "REML",  
            na.action = na.exclude)
```

```
anova(lm.1, lm.2) # lm.2 is clearly superior (p<0.001)
```

```
#### FINAL MODELS ####
```

```
##### for long full subset
```

```
lm.long <- lme(form_s,  
              data = subs.long,  
              random = ~ 1 | ID,  
              method = "REML",  
              na.action = na.omit)
```

```
summary(lm.long)
```

```
r.squaredGLMM(lm.long)
```

```
plot(lm.long)
```

```
##### for short full subset
```

```
lm.short <- lme(form_s,  
               data = subs.short,  
               random = ~1 | ID,  
               method = "REML",  
               na.action = na.exclude,  
               control= lmeControl(opt='optim'))
```

```
summary(lm.short)
```

```
r.squaredGLMM(lm.short)
```

```
plot(lm.short)
```

```
##### for low competition subset
```

```
lm.low <- lme(form_s,  
              data = subs.low,  
              random = ~ 1 | ID,  
              method = "REML",  
              na.action = na.exclude)
```

```
summary(lm.low)
```

```
r.squaredGLMM(lm.low)
```

```
plot(lm.low)
```

```
##### for high competition subset
```

```
lm.high <- lme(form_s,  
               data = subs.high,  
               random = ~ 1 | ID,  
               method = "REML",  
               na.action = na.exclude)
```

```
summary(lm.high)
```

```
r.squaredGLMM(lm.high)
```

```
plot(lm.high)
```