Assessing the impact of urban heating on tree growth in Berlin with open inventory and environmental data

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01 December, 2021

**This document outlines the rationale for an analysis of tree growth (potential) and its relationship with the Urban Heat Island (UHI) effect in Berlin using an extensive, publicly available data set. It introduces preliminary results and provides an outlook for up-coming and potential work.**

# 1 Introduction

The manifold ecological and societal benefits urban trees provide (e.g., Roy et al., 2012) depend critically on their health and performance. For instance, trees alter local energy budgets (Grimmond et al., 1996 ; Hertel and Schlink, 2019) through shading and transpiration (Endlicher et al., 2016; Gillner et al., 2015), and therefore can reduce ambient temperatures, infrastructure power-consumption and (human) thermal discomfort (Akbari et al., 2001; e.g. Gulyás et al., 2006; Hoyano, 1988; Mayer and Höppe, 1987). However, excess heat common for cities (i.e., Urban Heat Island, UHI, Oke, 1982), combined with other urban conditions, affects tree physiological functioning with outcomes ranging from enhanced growth to early senescence, branch die-back, and even mortality (Au, 2018; Gillner et al., 2014; e.g., Hilbert et al., 2019). Thus, assessing the effect of increased temperatures on trees, as part of urban green infrastructure, is instrumental for understanding as well as adapting to current and expected conditions in this century (Ward and Johnson, 2007), especially considering ever more urbanized societies and the potential for UHI effects to compound with more frequent atmospheric drought (Brune, 2016; Norton et al., 2015; Roloff et al., 2009).

The UHI effect, i.e., the difference between urban and adjacent rural (air) temperatures, has been intensively studied for several decades (cf. Oke, 1982; Stewart, 2011). It is typically related to the structure and density of urban land-use (Kuttler et al., 2015), which can be characterized through local climate zones, and modulated by physiographic and urban characteristics, such as vicinity to water bodies, predominant wind and street direction, etc. (Stewart and Oke, 2012); yet, the physical basis for the excess heat in cities is to a large extent found in the altered surface energy balance as the proportional cover of vegetation decreases compared to rural (or reference) systems (Hertel and Schlink, 2019; Oke, 1992). In temperate climates, this results in strongest UHI magnitudes at night (cf. Fenner et al., 2014). For example, Berlin features the most intense UHI in Germany due to its large extent and development intensity with an average air temperature increase of around 5 K at night-times (2001-2010) with maxima of up to 11 K (Fenner et al., 2014) in urban rural areas.

Increased air temperatures due to UHIs can affect tree growth through altering several physiological processes across plant organs directly or indirectly (Dusenge et al., 2019). Generally, reaction times at cellular level increase with temperature up to a maximum, after which a drop in enzymatic activity results in a species-dependent optimum curve (Arcus et al., 2016; Parent et al., 2010). In leaves this optimum response is reflected in the net assimilation rate of carbohydrates, as a balance of photosynthesis and respiration, with losses exceeding gains more rapidly with increasing temperatures (Long, 1991). These responses vary between species (Tjoelker et al., 2001) as well as intra-specifically due to local acclimation, i.e., a shift of optimum temperature responses after prolonged exposure (Yamori et al., 2014), and threshold temperatures before tissue damage occurs (for review see Geange et al., 2021). High temperatures in temperate areas are often coincident with low relative air humidity (i.e., large vapor pressure deficit), which in turn can decrease stomatal conductance governing the majority of gas exchange in leaves (Grossiord et al., 2020), and thus the capacity for photosynthesis. Under prolonged stomatal closure (or decreased conductance) with high temperatures, trees may thus face decreased growth (in subsequent years) or even starvation as their carbohydrate reserves are depleted yet not replenished at sufficient rates (McDowell et al., 2008). Furthermore, air (and soil temperatures) affect the initiation, speed and cessation of cambial activity, and thus radial growth throughout a growing season (e.g., see Begum et al., 2013; Rathgeber et al., 2016). Radial growth is increasingly considered to be limited by wood formation dynamics and their relation with environmental drivers, rather than solely by photosynthetic activity (Körner, 2015). In particular, the availability of soil water is critical for cell expansion (e.g., Peters et al., 2021) and most likely limits radial growth before photosynthesis (Fatichi et al., 2014); however, this water availability is again linked to local climate as higher temperatures drive evaporation and thus may contribute to the depletion of soil water storage, impeding growth.

Urban trees show a tendency for enhanced growth rates and/or productivity compared to rural conspecifics (e.g., Briber et al., 2015; O’Brien et al., 2012), which is typically attributed to increased temperatures (Jia et al., 2018; Pretzsch et al., 2017), yet feature a broad range of effect sizes and signs (i.e., reduced growth) specific to species and location. Zhao et al. (2016) showed that productivity rates, as a proxy for growth, increased within urban clusters as urbanization intensifies using remotely sensed vegetation indices. Further, Moser-Reischl et al. (2019) identified positive associations between air temperature and radial growth for two species (total of 20 individuals) commonly selected by urban planners (*Tilia cordata* MilL., *Rubinia pseudoacacia*) in Munich. Contrastingly, Gillner et al. (2014) highlight decreased growth for *Acer* species (*A. platanoides* and *pseudoplatanus*), *Platanus x hispanica* and *Quercus rubra* with higher summer temperatures of the preceding year, especially when compounded with drought, in another German metropolis (Dresden). Quigley (2004) identified absolute growth potential decreased for species between rural and urban conspecifics, yet assessments were limited to comparatively small sample sizes per group ( divided in 15 species, 3 groups and 2 locations). Pretzsch et al. (2017) inferred enhanced growth in recent decades and across urban locations spanning several latitudes, including Berlin - however, only 145 individuals of one species (*T. cordata*) were assessed there. As mentioned previously, climate-growth relationships can vary substantially between species, and in fact, Quigley (2004) and Pretzsch et al. (2017) report contrasting results regarding average tree diameter, i.e. smaller or larger for urban rural trees of same age. Similarly, for Berlin, Dahlhausen et al. (2018), identified enhanced growth in highly urbanized environments (using basal area increments of a large sample of 252 trees) for *T. cordata*, the most abundant tree of the city, which they attributed to the UHI effect, while intermediate development intensity was adverse for tree growth. These differences in growth trends may result from contrasting species-specific responses to increased temperatures, but are indeed affected by other (time-varying) factors and stochastic processes, such as water availability, pollution and road-salt loading, structural impedance by infrastructure, or management, etc. (Pauleit et al., 2002; Quigley, 2004; Randrup et al., 2001; Rhoades and Stipes, 1999). Further, the variability in responses may require that assessments are developed for a specific region, because well-understood tree characteristics (e.g., see Brune, 2016; Roloff et al., 2009), could be strongly modulated predictably due to management, planting practices, or other environmental controls; for example, if drought hardiness is related to extensive root networks, restricted soil volumes available to street trees will render a species more vulnerable to water stress.

Space-for-time substitutions and time series comparisons between and within locations are a common approach (cf. studies above) to generate inferences in observational (rather than treatment-control) studies, where manipulations are costly or logistically unfeasible due to time and/or financial constraints. However, they require accounting for confounding factors specific to trees’ environments, such as street characteristics, development intensity, available soil volume, etc. While several of the aforementioned studies applied these approaches to quantify temperature and excess heat on growth, they typically compare trees grouped using qualitative or summary descriptors of sampling sites, disregarding the spatio-temporal variability in location-specific factors noted above. This can hinder the extrapolation from individual sampling sites toward predicting effects across entire urban areas and tree stocks, especially when studies rely on labor-intensive methods, which are limited logistically by sampling effort, reducing sample sizes and coverage of species and space. This can be exacerbated by a lack of co-located environmental variables (i.e. measured in situ) at pertinent spatial scales, for instance, as noted by Wohlfahrt et al. (2019) for air temperature and tree leaf phenology, which may lead to incorrect inferences and interpretations for the role of climate change on growth/productivity when applying space-for-time substitutions. It is thus likely that the varying and even contrasting growth responses observed for urban trees across and within studies are at least modulated by some confounding factors, making the attribution to a single driver, such as excess heat, more difficult and possibly less accurate.

These limitations could be overcome by developing extensive dendroecological surveys (i.e., incremental growth) and/or inventories (single or repeat) combined with pertinent environmental data with adequate spatio-temporal coverage and resolution. Inventories are logistically and financially more feasible, and - together with environmental data - are increasingly more available (e.g. Ossola et al., 2020) due to open data policies and their value being recognized across domains for urban greenspace planning and adaptation (Hansen et al., 2019; Monteiro et al., 2020). Berlin, as one of the greenest cities in Europe, provides an openly accessible tree inventory, with spatio-temporal environmental data sets relevant to tree growth. It features a total of 650000 individuals covering 94 genera and at least 600 species and/or cultivars, listing information on location, stem diameter (at breast height; ), and stem height, amongst other variables, for the majority of street and park trees. For this study, our objective was to assess the impact of excess urban heat, i.e. the UHI effect, on tree growth () using this openly available inventory data set, complemented by additional open data sources as well as incremental growth data from tree cores. The assessment relied on flexible statistical models that could capture species and location-specific responses to heat and other urban factors. Specifically, we aimed to (1) assess heat exposure of the most abundant species; (2) determine the impact of (excess) heat on stem growth across tree age classes with a space-for-time substitution; (3) highlight the role of location-specific environmental factors in mediating temperature responses. Our results are a contribution toward Berlin’s current and future management of its tree stock and may help drive adaptation to climate change. Despite being a case study for a single city, we believe our work may provide a flexible approach for other cities with available or growing inventories, as well as ancillary environmental data, and may also inform the use of other planning tools, such as species-climate matrices (Roloff et al., 2009) regarding temperature sensitivity.

# 2 Methods

## 2.1 Study area

Berlin is one of the largest metropolitan areas in Central Europe (892) with a population of approximately 3.6 million, and a maximum extent of 38 in North-South and 45 in East-West directions. It is located in North-Eastern Germany, and lies in the temperate zone with warm-humid climate (Dfb) according to the updated Köppen-Geiger classification (Beck et al., 2018), with mean annual temperature of approximately 10 and precipitation of 575 (Tempelhof weather station, DWD). Berlin features low relief (approximately 30 to 60 with 120 at solitary peaks), and is centered around a glacial outwash valley (sands, gravel), bordered by two plateaus consisting of glacial till and clay in the North-East and South, as well as sands in the South-West. The city provides extensive public green space covering around 30 of its area (SUVK, Berlin, 2019), with an extensive urban forest of nearly 700000 publicly-managed trees along streets, in parks and in riparian areas.

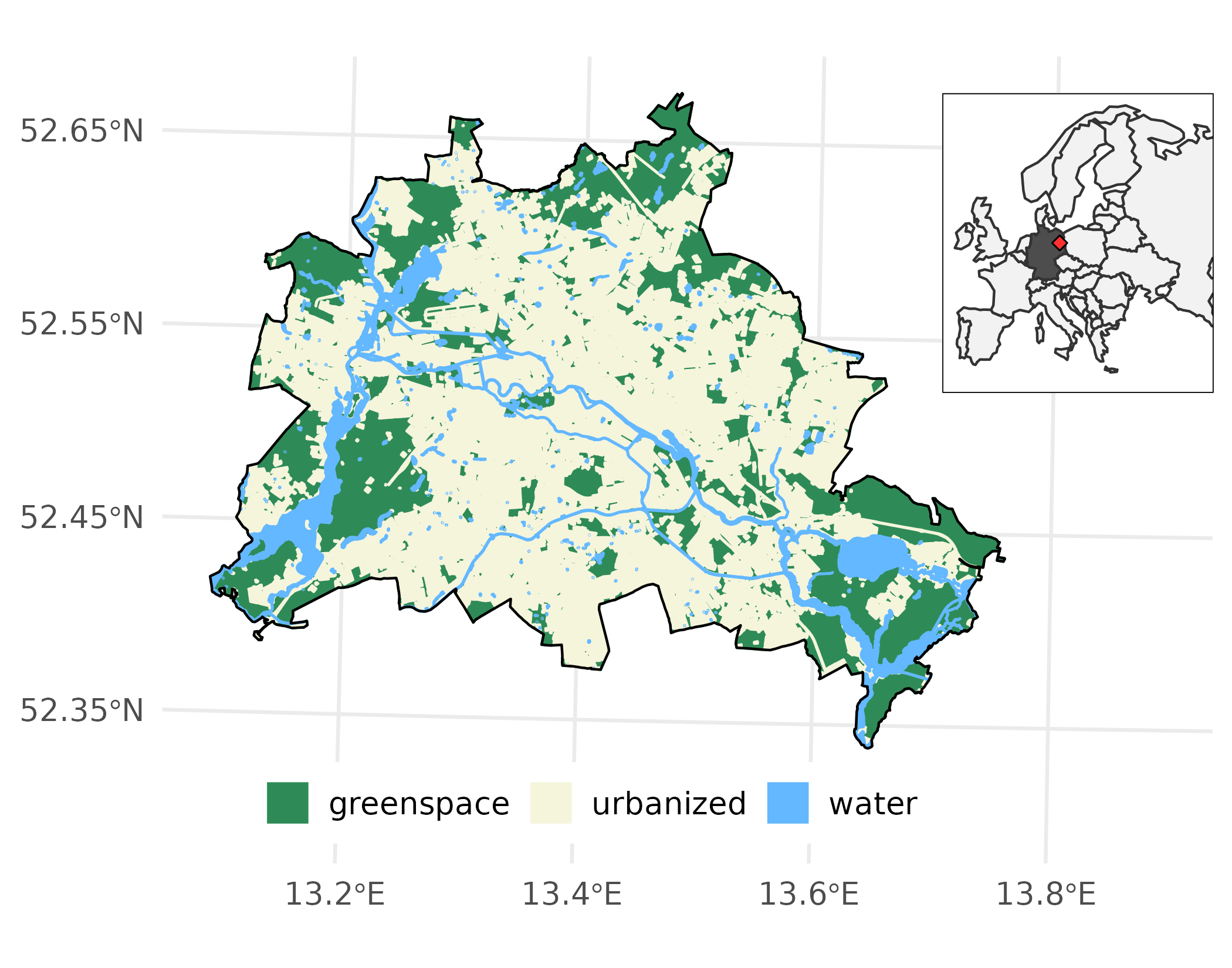


Figure 2.1: Berlin’s generalized land-use derived from SUVK, Berlin (2019) and location within the European context (inset).

## 2.2 General approach: space-for-time analyses

We modeled the stem diameter () of Berlin’s ten most abundant species (contingent to ancillary data availability) in relationship to their location, age, a measure of excess heat (UrbClim by De Ridder et al., 2015; Berlin Environmental Atlas models; LandSat-derived surface urban heat island by Chakraborty and Lee, 2019), and additional environmental covariates with generalized additive models (GAMs, see Section2.5 for details). Covariates were extracted at 150 and 300 to infer the impact of reference scale of the urban fabric on tree growth. From all tested models the most suitable (i.e., parsimonious with highest explanatory) was employed for further analyses.

## 2.3 Data sources

An overview of data used for models, including sources, types, and application, is provided in Table2.1, with detailed descriptions in the following subsections.

Table 2.1: Data description used for maps/visualizations and analyses. Resolution and radius are provided in , the latter is the buffer in which data was averaged around each trees. A zero-radius refers to a point extraction from categorical and location specific data. Polygons with radius data were rasterized to a resolution of

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Name | Accessed | Type | Unit | Resolution | Radius | Source | Reference |
| Street Trees | Oct ’20 | Point |  |  |  | <https://daten.berlin.de/> |  |
| UHI Berlin | Dec ’19 | Raster |  | 500 | 150 | <https://yceo.yale.edu/research/global-surface-uhi-explorer> | Chakraborty et al. (2019) |
| UHI Berlin | Dec ’19 | Raster |  | 500 | 150 | <https://yceo.yale.edu/research/global-surface-uhi-explorer> |  |
| Berlin Climate Model, Air temperature 2015 (Umweltatlas) | Feb ’21 | Polygon |  | 5 | 150 | <https://daten.berlin.de/> |  |
| UrbClim ERA5 Model Output (ECMWF, UCSC) | Mar ’21 | Raster |  | 100 | 150 | <https://cds.climate.copernicus.eu/> | Deridder et al. (2015) |
| Berlin Land-use | Apr ’21 | Polygon |  |  |  | <https://daten.berlin.de/> |  |
| Copernicus CORINE CLC | Mar ’21 | Raster |  | 100 |  | <https://land.copernicus.eu/> |  |
| WUDAPT LCZ | Oct ’20 | Raster |  | 100 | 150/300 | <https://www.wudapt.org/continental-lcz-maps/> | Demuzere et al. (2019) |
| Berlin Veg/Building Height | Oct ’20 | Polygon |  | 5 | 150/300 | <https://daten.berlin.de/> |  |
| Berlin Soil Nutrients, |  |  |  |  |  |  |  |
| Bodenkundliche Kennwerte 2015 (Umweltatlas) | Nov ’20 | Polygon |  |  | 0 | <https://daten.berlin.de/> |  |
| Planting Bed Area | Oct ’20 | Polygon |  |  | 0 | <https://daten.berlin.de/> |  |
| Berlin Soils | Oct ’20 | Polygon |  |  | 0 | <https://daten.berlin.de/> |  |
| Berlin Districts | Oct ’20 | Polygon |  |  |  | <https://daten.berlin.de/> |  |
| Berlin Transport Network | Feb ’21 | Polygon |  |  |  | OpenStreetMap Overpass API |  |
| Berlin Water (Ways) | Feb ’21 | Polygon |  |  |  | OpenStreetMap Overpass API |  |

### 2.3.1 Street trees

Berlin’s open data provided tree inventories including species, age, location, and circumference which was transformed into diameter. Note that only street trees in urban, not rural areas or within green spaces, were considered here, but individual trees may grow along streets adjacent to green spaces and parks of varying sizes. Implausible observations, likely from erroneous data entry, were removed. Additional manual data processing for quality control was done with a bespoke software datacleanr by Hurley *et al*. (submitted), where obvious outliers or clearly interpolated data were removed; the latter was deemed necessary, as several observations in multiple city districts were derived by linear relationships (i.e., straight-line), which do not capture the ontogenic growth dynamics of trees, and leave no variation related to variables other than age. All of these operations were recorded, and can be viewed and reproduced via the supplementary code. Lastly, observations with unlikely diameter-age combinations were identified via the residuals of a generalized linear model between diameter and age with a Gamma log-link distribution: if individual residuals exceeded seven times the median absolute deviation of all residuals, they were removed. The median absolute deviation (MAD) is comparable to the inter-quartile range, yet more robust to outliers:

This approach is considered conservative (see supplementary information), yet all analyses were carried forward with the unfiltered and filtered data - no considerable differences were found, thus subsequent sections are based on the filtered data. Table2.2 shows the binned distribution of genera across age classes. Final samples applied in models were smaller, following the availability of ancillary data for a given observation, and limited to a maximum age of 125 years to increase confidence in reported values, and ultimately model estimates.

Table 2.2: Binned age-distribution for genera in Berlin data set, and entries missing age information.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Genera | (0,30] | (30,60] | (60,90] | (90,120] | (120,150] | 150+ | Total (n) | Missing (n) |
| Tilia | 40128 | 60854 | 34599 | 4390 | 120 | 11 | 140232 | 130 |
| Acer | 23306 | 33771 | 10220 | 1798 | 62 | 17 | 69330 | 156 |
| Quercus | 8686 | 16107 | 5721 | 2595 | 562 | 157 | 33873 | 45 |
| Platanus | 4467 | 11836 | 4784 | 1449 | 805 | 68 | 23425 | 16 |
| Aesculus | 4464 | 7064 | 5566 | 1211 | 91 | 25 | 18427 | 6 |
| Betula | 2469 | 7155 | 897 | 36 | 2 | 1 | 10572 | 12 |
| Fraxinus | 4324 | 3332 | 742 | 131 | 6 | 0 | 8543 | 8 |
| Robinia | 2494 | 4523 | 857 | 83 | 3 | 1 | 7975 | 14 |
| Carpinus | 3905 | 2349 | 176 | 4 | 0 | 0 | 6466 | 32 |
| Prunus | 3792 | 2121 | 111 | 12 | 0 | 0 | 6067 | 31 |
| Populus | 639 | 3559 | 991 | 279 | 17 | 14 | 5515 | 16 |
| Pinus | 422 | 1349 | 463 | 27 | 0 | 1 | 2269 | 7 |
| Other | 22337 | 12620 | 1799 | 448 | 61 | 17 | 37554 | 272 |
| Marg. Totals | 121433 | 166640 | 66926 | 12463 | 1729 | 312 | 370248 | 745 |

### 2.3.2 Temperature/UHI data

Temperature and UHI data were summarized temporally either by the provider or manually to provide a characteristic representation of heat loading during summer at different times (morning, afternoon/day, night), from which tree averages (radius of 150) were calculated (Figure2.2). Two data sets of urban air and one surface temperature were tested as explanatory variables in GAM models. The air temperatures from the Berlin environmental atlas (EnvAt) are model outputs that are representations of typical summer conditions at 0400, 1400 and 2200 hours; these data are provided at city block basis (spatial polygons), from which weighted averages were extracted. UrbClim air temperatures are hourly model outputs (100 resolution, De Ridder et al., 2015) based on ERA5 re-analyses data (ECMWF) for which observations from the hottest month available (June, 2011) were averaged to hours equivalent to Berlin Environmental Atlas (referred to as Berlin EnvAt) data by using a window of hour (i.e., 0300 to 0500, etc.). Subsequently, a land-use and land-cover mask (CORINE; European Union, Copernicus Land Monitoring Service 2018, European Environment Agency) was used to define urban and rural/forested areas. Using this mask was deemed reasonable as Berlin’s built-up area has not changed markedly over the past 50 years, i.e., about 52 to 61 (Mohamed, 2017). The urban heat loading was then calculated as

where is temperature () and define an urban grid cell. The LandSat-derived surface UHI data set by Chakraborty and Lee (2019) (referred to as LandSat) estimates its measure in a similar fashion and the reader is referred to the detailed description therein; note this data set provides day and night-time averaged UHI estimates at 500 resolution, which were extracted for the hottest summer in this record (2007).



Figure 2.2: Temp overviews; rows are landsat, berlin environmental atlas, and UrbClim, columns are morning, day/afternoon, night. **ADD Labels for Data source and time of day at left and bottom**

### 2.3.3 Ancillary environmental data

Following the general approach described above, four ancillary covariates next to a temperature measure were employed in models; these were chosen due to their availability at high spatial resolution and coverage, and/or because their influence on growth was previously identified in literature or their likely impact could be deduced using ecophysiological principles. We included planting bed area and the sum of exchangeable basic cation as a proxy for soil nutrient availability (point extractions), as well as the proportional coverage of local climate zone 6 (LCZ6; open mid-rise, see Demuzere et al. (2019) and Stewart and Oke (2012) for details) and adjacent building height (spatial averages). The latter was chosen as an increase reflects a transition away from densely urbanized areas and had the highest coverage for the processed tree inventory.

## 2.4 Dendrochronological sampling

To contextualize tree growth patterns between age groups derived from Berlin’s inventory data, we drew upon a recently established data set from Schneider *et al.* (in review), who sampled several common tree species across a rural-urban gradient. For our purposes, we grouped trees sampled in parks, green spaces and along streets into a single urban category, and focused analyses on these. Two to three cores were extracted at breast height from each tree. These were then prepared using standard dendro-ecological methods (i.e., mounting, sanding, measuring), and cross-dated with TSAP-Win and COFECHA (Holmes et al., 1986), producing mean tree series of incremental growth. Additionally, cambial age of each increment was established by counting years from the inner most ring at the pith () outward; on tangentially bored cores, missing rings to the pith were estimated.

Table 2.3: Overview of urban sampling locations and respective tree species coverage. Individual trees were sampled two or tree times to obtain a mean-tree ring width series.

|  |  |  |
| --- | --- | --- |
| Location | Species | n |
| Alpenrose | Quercus robur | 15 |
| Grünanlage Britz-Süd | Fagus sylvatica | 17 |
| Grünanlage Britz-Süd | Pseudotsuga menziesii | 17 |
| Grünanlage Britz-Süd | Fraxinus excelsior | 14 |
| Grünanlage Britz-Süd | Pinus sylvestris | 16 |
| Grünanlage Britz-Süd | Larix decidua | 16 |
| Grünanlage Britz-Süd | Tilia Cordata | 16 |
| Grünanlage Britz-Süd | Quercus robur | 15 |
| Grünanlage Britz-Süd | Quercus petraea | 21 |
| Hasenheide | Quercus robur | 12 |
| Hasenheide | Quercus robur | 14 |
| Spielplatz Weigandufer & Wildenbruchplatz | Fraxinus excelsior | 19 |
| Werrastraße | Fraxinus excelsior | 12 |

## 2.5 Statistical Analyses

### 2.5.1 GAMs

We applied hierarchical generalized additive models (GAM) to estimate the relationship of several covariates with stem diamater growth (). GAMs, as an extension of generalized linear models (Wood, 2017), allow modeling response variables as parametric and non-parametric combinations of smoothed explanatory covariates, and can assume non-normal response distributions. These smooths are constructed by summation of base functions of varying complexity and form, analogous to scatterplot smoothing (Hastie and Tibshirani, 2017), which provides a high degree of flexibility, ideal for fitting ecosystem dynamics which are rarely linear (Pedersen et al., 2019), or correctly represented with deterministic functional forms (e.g. quadratic equations). In general, a GAM can be written as:

and

where is taken from an appropriate distribution and corresponding link function , is the intercept and represents a smooth function of a predictor (Pedersen et al., 2019), and . Nested data structures (e.g., city districts) can be accounted for by introducing random effects, while spatial dependence between observations can be accounted for by constructing smoothing functions with, for instance, northings and eastings (cf. Wood, 2017). All models were implemented in R (R Core Team, 2021) using functions available in the package mgcv (Wood, 2017).

### 2.5.2 Dendrochronological analyses

We assessed trends in annual growth dynamics of urban trees across the 20 century for 1920-1960 and 1961-2001 Dahlhausen et al. (2018) with a hierarchical GAM implemented in mgcv::gamm() to leverage auto-correlation structures made available through the package nlme (Pinheiro et al., 2021). Annual growth was modeled as:

where is a log-link for , is the annual radial increment for observation . A global temporal (by year) and time-dependent (, or ) trend in cambial age were implemented with thin plate regression splines (default smoothing function in mgcv); is a time-group dependent intercept, while represents a matrix of random effect coefficients for species to account for differences in growth patterns, and . A -order autocorrelation-moving average (ARMA) correlation structure was applied (i.e., ) to account for the dependency of across years for each tree, as is frequently the case for tree growth (e.g., see Fritts and Swetnam, 1989); the detailed implementation for this model is given in the supplemental material code. was then derived for a range of cambial ages, and averaged for both time groups, allowing a comparison of recent to earlier growth. We acknowledge that tree cores obtained at breast height do not represent absolute tree age. However, here they serve as a proxy for growth between young () and older individuals to contextualize growth patterns inferred from the larger-scale tree inventory.

### 2.5.3 Stem diameter model development and selection

The diameter () of the ten most abundant species were modeled using GAMs as follows:

where is a log-link for , and , are indices for observations and species, respectively, and refers to an (excess) heat measure from UrbClim, Berlin EnvAt or LandSat at different times (morning, afternoon/day, night; cf. Section2.3); is a species-dependent intercept, while represents a matrix of random effect coefficients for districts to account for differing management regimes across the city. A global spatial smooth (representing projected coordinates in UTM) via a Gaussian process (cf. p. 242 in Wood, 2017) was included to account for the spatial structure of observations, which reduced auto-correlation of model residuals considerably (see supplemental information). These were compared to a sub-set of models without a spatial component (cf. Equation(2.7), and Figure3.2 but not further discussed there). We also tested a suite of models without the spatial smooth for comparison **what’s the impact of remaining auto correlation? inflated errors, larger coefficients?**

Further, we implemented the interaction between temperature and age (i.e., as tensor smooths (Wood, 2006) to account for the different variable scales (i.e., units); all models were also tested without this interaction using a thin plate regression spline smooth for temperature (not shown in equations above). The functions are for species-specific smooths (i.e., with individual smoothness penalties and functional shapes as detailed by Pedersen et al., 2019). The covariates for planting bed area and soil nutrient availability were log transformed to account for their skewed distribution, improving the estimation of coefficients for their respective basis functions. Note, that Equation(2.9) was considered as the appropriate null model for interpretations. Models were implemented with mgcv::bam() (Li and Wood, 2020; Wood et al., 2017) and readers are referred to the detailed implementation in the supplemental material code.

Considering all combinations of (excess) heat measures and covariates (with point, as well as 150/300 extractions), a total of 158 models were applied. We selected the model with the highest explanatory power, based on residual deviance and observed vs. predicted fit, with comparatively largest sample size for final analyses. From this model we derived age and species dependent averages across a temperature measure from predicted values in 5-year age groups starting at 30, 45, 60, 75, 90.

As the spatial extent and coverage varied between temperature and ancillary data, more complex models (and specifically those including planting bed area and LandSat temperatures) typically also had fewer total observations. While this prevented a full comparison with information-based model selection criteria, such as Aikake’s (AIC), the appropriateness of models that differed only in their implementation of the temperature-age interaction (i.e., ) could be assessed. For this reason, the suite of developed models presented above were limited to comparatively simple structures (i.e., few terms, interactions and restricted number of basis functions), reducing the potential for choosing over-fitted models without formal comparison. AIC is calculated as:

where is the maximum likelihood estimate, and is the number of parameters. Where any two comparable models had a , we considered the model with the lower score more suitable. Future research may focus on collecting additional data (e.g., increasing the coverage on planting bed area) and subsequently deriving species-specific smooths for ancillary environmental covariates. We chose to carry out the analysis in its current form rather than on considerably smaller but comparable sample sizes across models, to identify the strongest relationships in the existing data. This allowed us to highlight the utility of the approach *per se* and for Berlin in particular. **Measures used to asses goodness-of-fit were residual deviance, RSME and MAE (add formuals)**

# 3 Results

## 3.1 Growth trend dynamics

Recently established annual, incremental growth is on average greater as compared to earlier times (i.e., prior 1960; Figure3.1). The contrast is strongest in the first 30 years of cambial development, with clear indication that averages are statistically different up to approximately 22 years (cf. overlap of 95confidence intervals). The predicted trajectories for both periods follow typical ontogenetic patterns, yet differ in shape. This may be due to inaccurately estimated cambial ages, explaining the largely monotonic decrease for recent growth due to missing the typical (but not always present) initial rise and fall in pith-near stages. This would inadvertently create a left-shift in Figure3.1 for recent growth. Assuming that to be the case, the actual difference in average rates would be greater than presented here.

(ref:cambial-effect) Rates for annual incremental growth differ between recent and earlier times, as predicted by a hierarchical GAM (see Section2.4). Thick lines and bands are for mean and 95 confidence interval of all annual predictions across a time group (fine lines). On average, early stages of recent growth (up to approximately 22 years) exceed that of earlier periods discernibly.

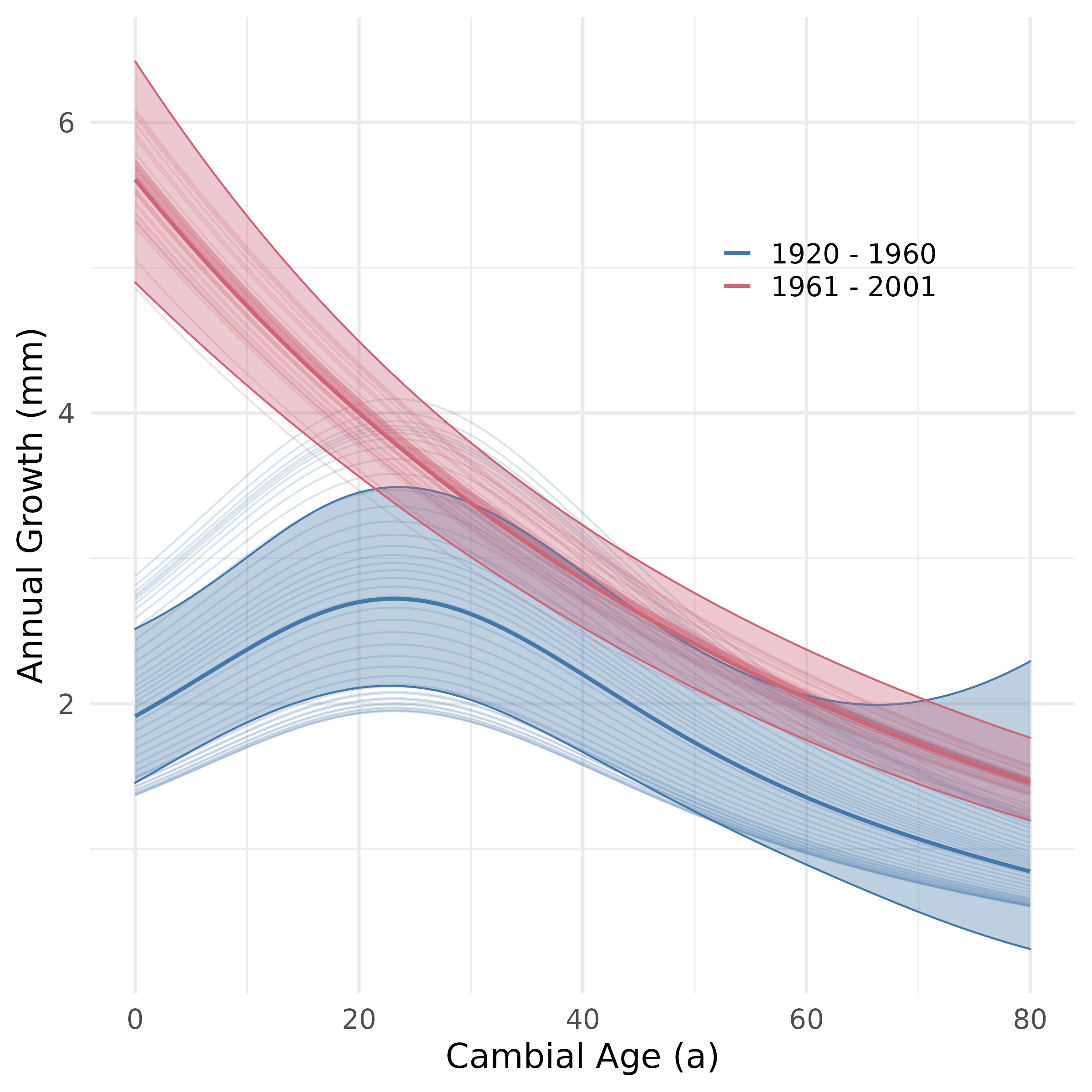


Figure 3.1: (ref:cambial-effect)

## 3.2 Model selection

* Null-model high, but for predictive purposes more is better
* Temperature-based models on average better than without, but planting bed area and lcz6 individually outperform - indication that these variables are indeed important; choice of best performing model, which includes lcz6, coroborated. \*Landsat temp best on average - easily accessible/maintainable as compared to model outputs
* vs.  - scale of impact (further investigation, note in discussion)
* building height, as a proxy for urban fabric and incoming radiation had minimal effect (regardless of 150/300)

(ref:model-deviance) Overview of model fit, expressed as explained deviance, for all tested models. The Panels distinguish between models without (top) and with (bottom) spatial smooths to account for autocorrelation of residuals. Colored sub-sections define models without and with the applied (excess) heat measures. Symbols identify models with an interaction between temperature and age (diamond), and without (circle), while colors highlight included covariates and their reference radius (i.e. 150/300, but also note x-axis labels), and size indicates the model’s observations. Generally, including temperature (interactions) improve model fits above the null-model (age only), and excluding planting bed area and LCZ6 cover, also above other non-temperature models. The LandSat-derived UHI measures provide the best fit on average, with the model including a temperature-age interaction and LCZ6 cover scoring highest.

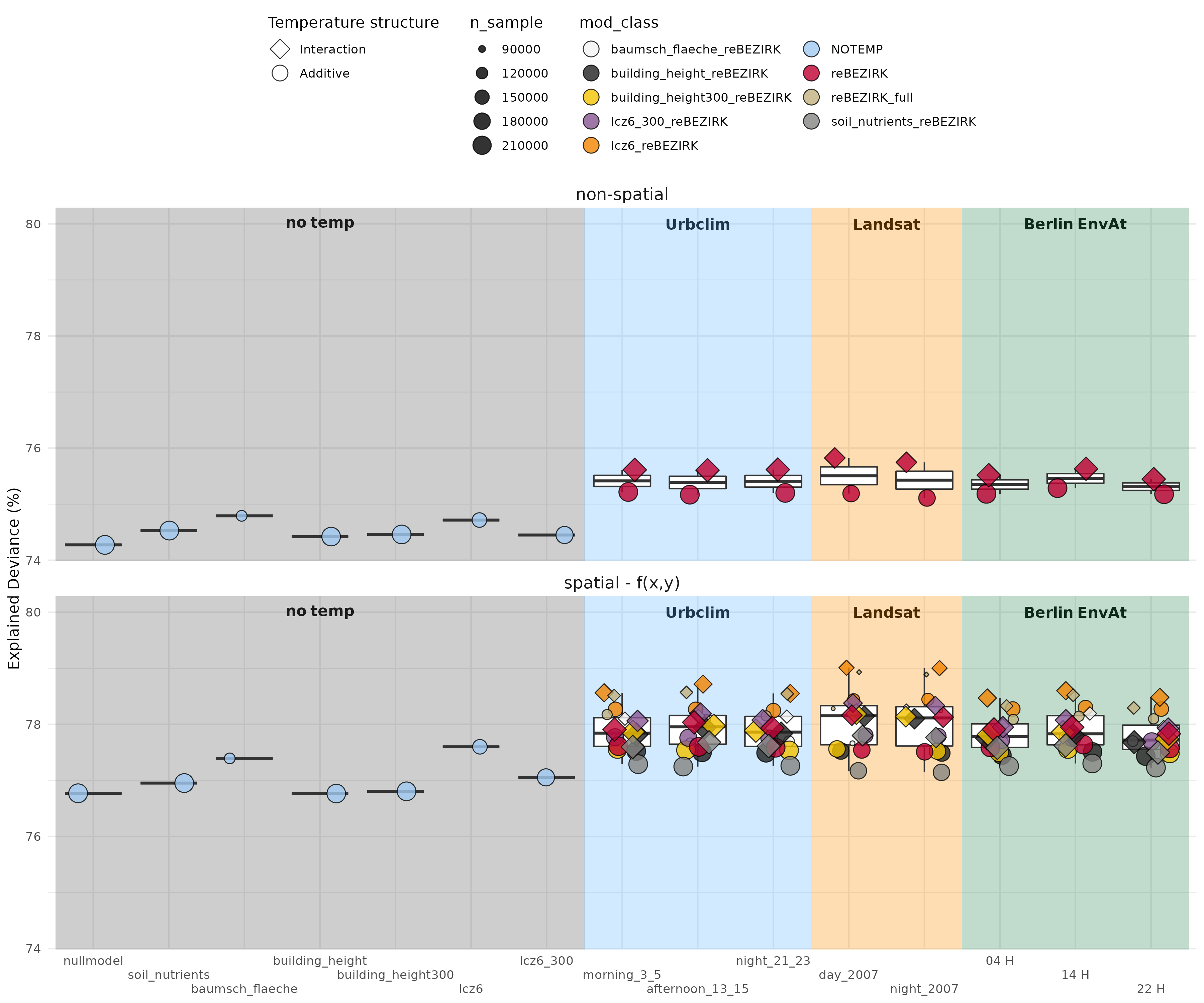


Figure 3.2: (ref:model-deviance)

**Add table with ANOVA for interaction, non-interaction and MAE/RSME**

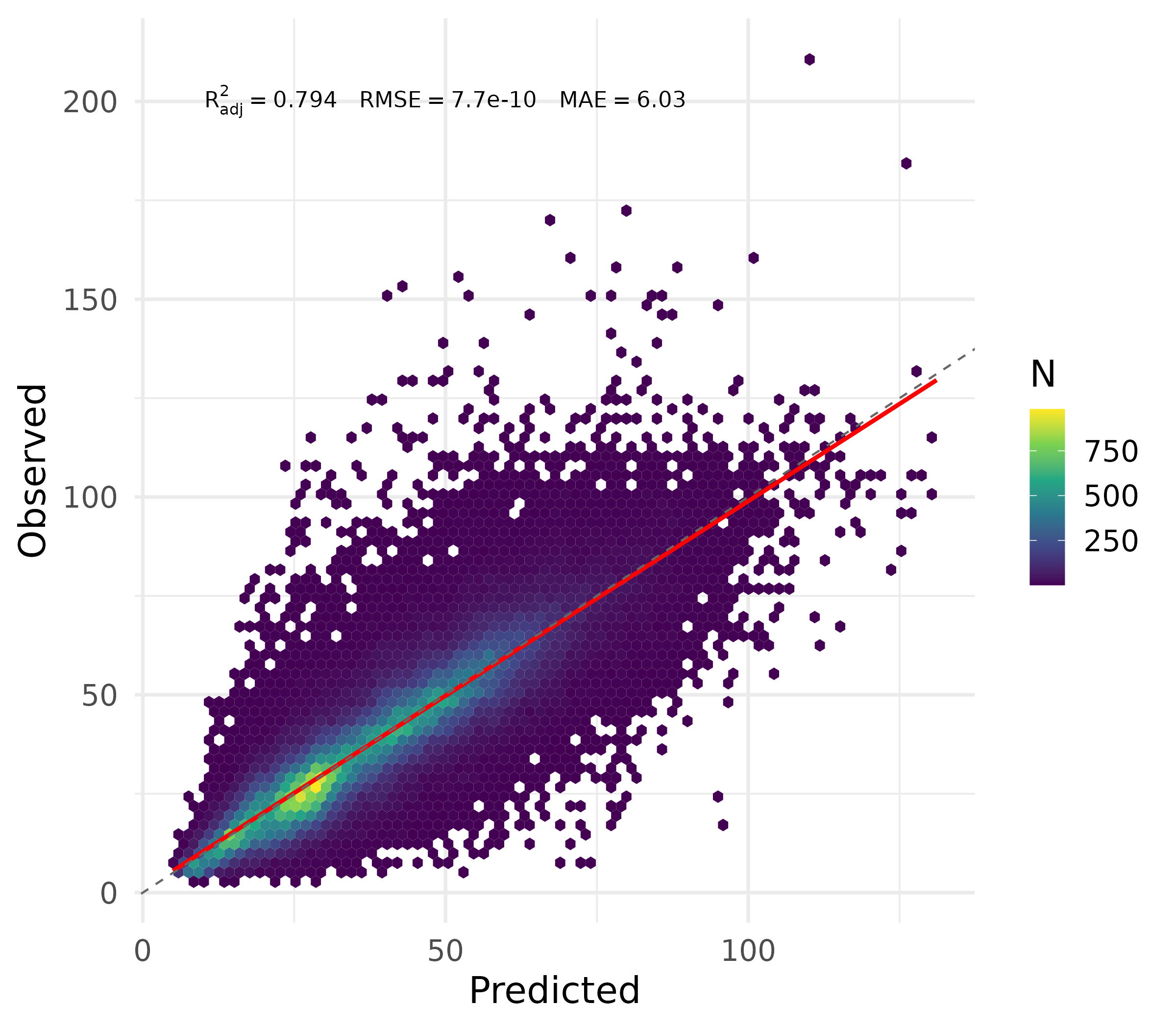


Figure 3.3: Predicted observed data for the best model according to explained deviance and ‘local’ AIC comparison, based on the LandSat-derived UHI measure (Chakraborty and Lee, 2019) for average summer conditions (2007) and LCZ6 [open to mid-rise; Stewart and Oke (2012)]. Hexagons and colors represent x-y bins (i.e., in the observed-predicted space) and their counts, and the red line is a least-squares fit. The model captures the mean response well, as indicated by lighters colors along dashed 1:1 line, and its close approximation by the least squares fit, as well as model metrics (see text label in plot). However, the generally large scatter around this mean response indicates that predictions on individual-level would be inappropriate.

## 3.3 Urban heat and urban fabric effects on stem growth

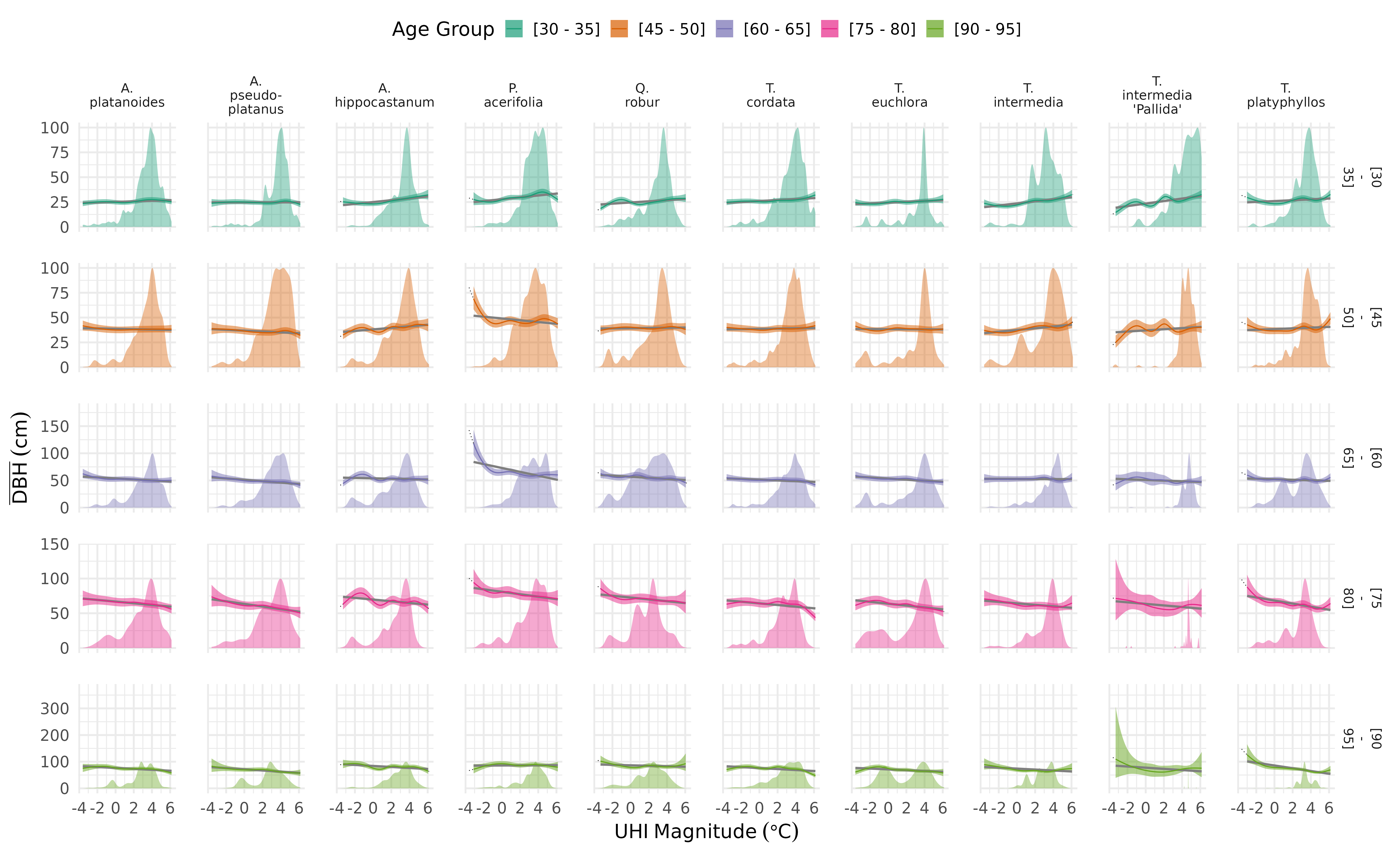


Figure 3.4: Age group-dependent temperature effect; only within range

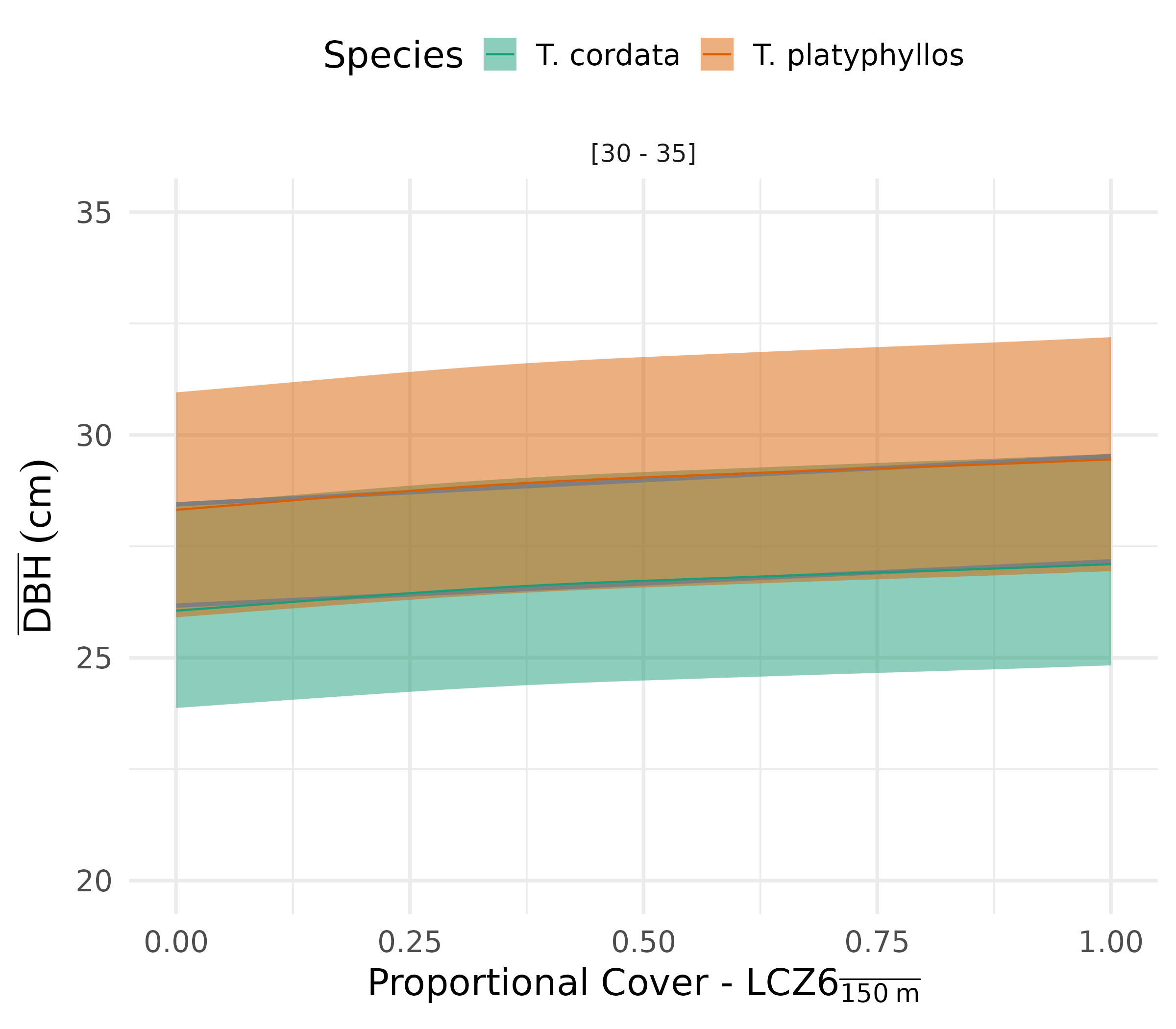


Figure 3.5: Global effect of LCZ6 on growth

## 3.4 Exposed trees

**Add figure with tree locations where growth is below the average - color = UHI?**

# 4 Discussion

1. Temperature, environmental and urban controls on tree growth
   * Intra specific differences
     + management
     + root vs. canopy (huber value?)
     + accelerated recent growth
     + comparison young vs. old -> increased CO2, perhaps limitation of space for time, as lower conductance under high CO2 may result in more water savings (check WUE in old vs. young trees? future direction).(Dusenge et al., 2019) (McCarthy et al., 2011)
   * Sensitive trees in hot spots
   * Temporal dynamics
   * Validity and limitations

* (Bussotti et al., 2014)

1. Implications:

* Policy / planning:
  + tree species
    - Increase temporal coverage and accuracy
      * which trees to prioritize for measurement campaigns
      * Supplement species matrix etc. with these analyses
* Open data important –> drives innovation

## 4.1 Conclusions

# 5 Acknowledgements

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##### 6.0.0.0.1 pagebreak

### 6.0.1 Colophon

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#> P KernSmooth 2.23-20 2021-05-03 [?] CRAN (R 4.0.5)  
#> P knitr 1.33 2021-04-24 [?] CRAN (R 4.1.0)  
#> P labeling 0.4.2 2020-10-20 [?] CRAN (R 4.1.0)  
#> P lattice 0.20-44 2021-05-02 [?] CRAN (R 4.1.0)  
#> P lifecycle 1.0.0 2021-02-15 [?] CRAN (R 4.1.0)  
#> P listenv 0.8.0 2019-12-05 [?] CRAN (R 4.1.0)  
#> P lme4 \* 1.1-27 2021-05-15 [?] CRAN (R 4.1.0)  
#> P lwgeom 0.2-5 2020-06-12 [?] CRAN (R 4.1.0)  
#> P magrittr \* 2.0.1 2020-11-17 [?] CRAN (R 4.1.0)  
#> P mapproj 1.2.7 2020-02-03 [?] CRAN (R 4.1.0)  
#> P maps 3.3.0 2018-04-03 [?] CRAN (R 4.1.0)  
#> P MASS 7.3-54 2021-05-03 [?] CRAN (R 4.0.5)  
#> P Matrix \* 1.3-3 2021-05-04 [?] CRAN (R 4.1.0)  
#> P matrixStats 0.57.0 2020-09-25 [?] CRAN (R 4.1.0)  
#> P memoise 1.1.0 2017-04-21 [?] CRAN (R 4.1.0)  
#> P mgcv 1.8-35 2021-04-18 [?] CRAN (R 4.1.0)  
#> P minqa 1.2.4 2014-10-09 [?] CRAN (R 4.1.0)  
#> P munsell 0.5.0 2018-06-12 [?] CRAN (R 4.1.0)  
#> P ncdf4 \* 1.17 2019-10-23 [?] CRAN (R 4.1.0)  
#> P nlme 3.1-152 2021-02-04 [?] CRAN (R 4.0.3)  
#> P nloptr 1.2.2.2 2020-07-02 [?] CRAN (R 4.1.0)  
#> P pals 1.7 2021-04-17 [?] CRAN (R 4.1.0)  
#> P patchwork \* 1.1.1 2020-12-17 [?] CRAN (R 4.1.0)  
#> P pillar 1.6.1 2021-05-16 [?] CRAN (R 4.1.0)  
#> P pkgbuild 1.1.0 2020-07-13 [?] CRAN (R 4.1.0)  
#> P pkgconfig 2.0.3 2019-09-22 [?] CRAN (R 4.0.2)  
#> P pkgload 1.1.0 2020-05-29 [?] CRAN (R 4.1.0)  
#> P plyr 1.8.6 2020-03-03 [?] CRAN (R 4.1.0)  
#> P png 0.1-7 2013-12-03 [?] CRAN (R 4.1.0)  
#> P prettyunits 1.1.1 2020-01-24 [?] CRAN (R 4.1.0)  
#> P processx 3.5.2 2021-04-30 [?] CRAN (R 4.1.0)  
#> P progress 1.2.2 2019-05-16 [?] CRAN (R 4.1.0)  
#> P ps 1.4.0 2020-10-07 [?] CRAN (R 4.1.0)  
#> P purrr \* 0.3.4 2020-04-17 [?] CRAN (R 4.0.2)  
#> P R.methodsS3 1.8.1 2020-08-26 [?] CRAN (R 4.1.0)  
#> P R.oo 1.24.0 2020-08-26 [?] CRAN (R 4.1.0)  
#> P R.utils 2.11.0 2021-09-26 [?] CRAN (R 4.1.0)  
#> P R6 2.5.0 2020-10-28 [?] CRAN (R 4.1.0)  
#> P ragg 1.1.3 2021-06-09 [?] CRAN (R 4.1.0)  
#> P raster \* 3.4-10 2021-05-03 [?] CRAN (R 4.1.0)  
#> P RColorBrewer 1.1-2 2014-12-07 [?] CRAN (R 4.1.0)  
#> P Rcpp 1.0.6 2021-01-15 [?] CRAN (R 4.1.0)  
#> P readxl \* 1.3.1 2019-03-13 [?] CRAN (R 4.1.0)  
#> P remotes 2.2.0 2020-07-21 [?] CRAN (R 4.1.0)  
#> renv 0.13.2 2021-03-30 [1] CRAN (R 4.1.0)  
#> P rgdal \* 1.5-18 2020-10-13 [?] CRAN (R 4.1.0)  
#> P rlang \* 0.4.12 2021-10-18 [?] CRAN (R 4.1.0)  
#> P rmarkdown \* 2.5 2020-10-21 [?] CRAN (R 4.1.0)  
#> P rnaturalearth \* 0.1.0 2017-03-21 [?] CRAN (R 4.1.0)  
#> P rprojroot 1.3-2 2018-01-03 [?] CRAN (R 4.1.0)  
#> P rstudioapi 0.11 2020-02-07 [?] CRAN (R 4.1.0)  
#> P Rttf2pt1 1.3.8 2020-01-10 [?] CRAN (R 4.1.0)  
#> P rvest 1.0.0 2021-03-09 [?] CRAN (R 4.1.0)  
#> P scales \* 1.1.1 2020-05-11 [?] CRAN (R 4.1.0)  
#> P sessioninfo 1.1.1 2018-11-05 [?] CRAN (R 4.1.0)  
#> P sf \* 0.9-6 2020-09-13 [?] CRAN (R 4.1.0)  
#> P signal 0.7-7 2021-05-25 [?] CRAN (R 4.1.0)  
#> P snow \* 0.4-3 2018-09-14 [?] CRAN (R 4.1.0)  
#> P sp \* 1.4-5 2021-01-10 [?] CRAN (R 4.1.0)  
#> P spacetime 1.2-5 2021-06-14 [?] CRAN (R 4.1.0)  
#> P stars \* 0.4-3 2020-07-08 [?] CRAN (R 4.1.0)  
#> P storr 1.2.4 2020-10-12 [?] CRAN (R 4.1.0)  
#> P stringi 1.5.3 2020-09-09 [?] CRAN (R 4.1.0)  
#> P stringr \* 1.4.0 2019-02-10 [?] CRAN (R 4.0.2)  
#> P svglite 2.0.0 2021-02-20 [?] CRAN (R 4.1.0)  
#> P systemfonts 1.0.2 2021-05-11 [?] CRAN (R 4.1.0)  
#> P testthat 3.0.4 2021-07-01 [?] CRAN (R 4.1.0)  
#> P textshaping 0.3.5 2021-06-09 [?] CRAN (R 4.1.0)  
#> P tibble \* 3.0.4 2020-10-12 [?] CRAN (R 4.1.0)  
#> P tidyr 1.1.2 2020-08-27 [?] CRAN (R 4.1.0)  
#> P tidyselect 1.1.0 2020-05-11 [?] CRAN (R 4.0.2)  
#> P txtq 0.2.3 2020-06-23 [?] CRAN (R 4.1.0)  
#> P units 0.6-7 2020-06-13 [?] CRAN (R 4.1.0)  
#> P usethis 1.6.1 2020-04-29 [?] CRAN (R 4.1.0)  
#> P utf8 1.1.4 2018-05-24 [?] CRAN (R 4.0.2)  
#> P vctrs 0.3.8 2021-04-29 [?] CRAN (R 4.1.0)  
#> P viridisLite 0.4.0 2021-04-13 [?] CRAN (R 4.1.0)  
#> P webshot 0.5.2 2019-11-22 [?] CRAN (R 4.1.0)  
#> P withr 2.4.2 2021-04-18 [?] CRAN (R 4.1.0)  
#> P xfun 0.24 2021-06-15 [?] CRAN (R 4.1.0)  
#> P XML 3.99-0.8 2021-09-17 [?] CRAN (R 4.1.0)  
#> P xml2 \* 1.3.2 2020-04-23 [?] CRAN (R 4.1.0)  
#> P xts 0.12.1 2020-09-09 [?] CRAN (R 4.1.0)  
#> P yaml 2.2.1 2020-02-01 [?] CRAN (R 4.0.2)  
#> P zoo 1.8-9 2021-03-09 [?] CRAN (R 4.1.0)  
#>   
#> [1] /home/hurley/\_work/renv/berlin.trees-c2f6692a/R-4.1/x86\_64-pc-linux-gnu  
#> [2] /tmp/RtmpiumPXm/renv-system-library  
#> [3] /tmp/Rtmp0emyYX/renv-system-library  
#>   
#> P ── Loaded and on-disk path mismatch.

The current Git commit details are:

#> Local: master /home/hurley/\_work/p\_024\_GFZ\_berlin\_trees/berlin.trees  
#> Remote: master @ origin (https://github.com/the-Hull/berlin.trees)  
#> Head: [13757e8] 2021-11-30: adjusting eqs