Species-specific effects of the Urban Heat Island on tree growth across Berlin

Alexander G. Hurley[a*], Ingo Heinrich[a]
[a] *Geoforschungszentrum Potsdam, Section 4.3, Germany*
* Corresponding author: hurley@gfz-potsdam.de

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Abstract

This document outlines the rational for an analysis tree growth (potential) and its relationship with the Urban Heat Island (UHI) effect in Berlin. It introduces preliminary results and provides an outlook for up-coming and potential work. .

Contents

1 Introduction

Berlin features the most intense Urban Heat Island (UHI) in Germany due to its large extent and development intensity (Kuttler et al., 2015), with temperature increases of up to 12 K during day-time and 6 K on average for night-times (2001-2010, Fenner et al., 2014) in urban *vs.* rural areas. Consequently, urban green (infrastructure) systems are subjected to increased heat more frequently, potentially affecting their process dynamics - either positively or adversely. Their performance and health, however, is closely tied to local energy budgets (Grimmond et al., 1996 ; Hertel and Schlink, 2019), which in turn are decisive for controlling human wellbeing (e.g. Maras et al., 2016), amongst other factors. Assessing the effect of increased temperatures on green infrastructure, as part of the urban landscape, is therefore instrumental for understanding, and ultimately mitigating, the potential impact of future warming on increasingly urban societies (Norton et al., 2015).

Trees, in particular, provide shading as well as transpirative cooling in their vicinity (Endlicher et al., 2016; Gillner et al., 2015; Oke, 1982), and therefore can reduce ambient temperatures, infrastructure power-consumption and (human) thermal discomfort (e.g. Gulyás et al., 2006; Akbari et al., 2001; Hoyano, 1988; Mayer and Höppe, 1987); simultaneously, they provide numerous other environmental, cultural and psychological services and/or benefits (see Tzoulas et al., 2007 for review). Further, recent tree growth dynamics as a proxy for on-going and future warming may provide an additional line of evidence to support the growing knowledge base on future climate-vegetation dynamics (Zhao et al., 2016) and may aid in mitigation and adaptation efforts (Brune, 2016; Pretzsch et al., 2017).

Trees and green infrastructure in urban areas show a tendency for enhanced growth rates and/or productivity compared to rural counterparts (Jia et al., 2018; Pretzsch et al., 2017), yet feature a broad range of effect size ranges and, in some cases, signs specific to species and locality. Zhao et al. (2016) showed that growth rates increased within urban clusters as urbanization intensifies using remotely sensed vegetation indices. Similarly, for Berlin, Dahlhausen et al. (2018), identified positive growth modulation in highly urbanized environments (using growth increments) for *Tilia cordata* Mill, the most abundant tree of the city, which they attributed to the UHI effect, while intermediate development intensity showed indications of being least favorable for tree growth. Further, Moser-Reischl et al. (2019) identified positive associations between air temperature and radial growth for two species commonly selected by urban planners (*T. cordata*, *Rubinia pseudoacacia*) in Munich. By contrast, 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). Differences in growth trends may result from contrasting species-specific characteristics, but are indeed affected by other processes and factors, such as water availability, pollution and road-salt loading, structural impedance through infrastructure or management, etc. (Pauleit et al., 2002; Quigley, 2004; Randrup et al., 2001; Rhoades and Stipes, 1999). Under climate change, atmospheric drought will likely be compounded with high temperatures - and intensified UHIs - more frequently, adding further stress to current urban disturbance regimes (Roloff et al., 2009).

Conditions affecting tree growth can vary greatly within urban areas or regions, and need to be accounted for when establishing relationships with pertinent drivers, such as the UHI effect. This typically complicates the extrapolation from individual sampling sites toward predicting effect sizes across entire urban areas and tree stocks. This is especially the case for studies reliant on labour-intensive methods which are limited logistically by sampling effort, reducing sample sizes, as well as species and spatial coverage.

To complement (existing) detailed dendroecological analyses of climate-growth relationships in Berlin for key species, we propose inferring growth modulation from a large data set in excess of 650000 individuals provided by the Berlin Senate Administration (Senatsverwaltung). This data set contains information on location, species, trunk diameter (at breast height; DBH), and height, amongst other variables for street and park trees. In a space-for-time substitution, growth of individual species can be assessed across the entire cite of Berlin, and related to effects of the UHI, while accounting for other location-specific factors, such as street characteristics, development intensity, available soil volume, etc. Comparable applications are found, for example, in Quigley (2004) and Pretzsch et al. (2017). The former inferred absolute growth potential for species across successional groups, and between rural and urban species, yet lacked spatially-explicit effect size estimates or predictions of maximum potential; Pretzsch et al. (2017) applied linear hierarchical models to infer growth modulation for different cities, time periods and locations (urban *vs.* rural).

By contrast, we propose applying a statistical model that is spatially explicit, while also allowing to account for the nested nature of the data set (e.g. streets and districts) as well as other pertinent factors (hierarchical, generalized additive model, see Section 2). This also allows to infer the absolute growth potential of species given, for example, a specific location, age or UHI magnitude. Tree-level growth data, however, is paramount in validating such relationships, and its inclusion in the model would also allow incorporating effects of varying climate.

2 Proposed methods and data requirements

2.1 General analyses

The proposed statistical method is from the class of hierarchical, generalized additive models (GAM, or GAMM for mixed models/hierarchical models). In these models combinations of continuous and categorical predictor variables can be summed to estimate a response. In particular, continuous variables that are linearly, as well as non-linearly related to the response can be represented by applying a transfer function, typically termed “smoothing function” (Wood, 2017); these are constructed using a number of base functions of varying complexity and form, 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:

$$E(Y) \;=\; g^{-1}\left(\beta_0 + \sum_{i=1}^{n} f_i(x_i)\right), \tag{1}$$

and

$$y \;=\; E(Y) + \epsilon, \tag{2}$$

where Y is taken from an appropriate distribution and corresponding link function g, β_0 is the intercept and f_i represents a smooth function of a predictor (Pedersen et al., 2019), and $\epsilon \sim \mathcal{N}(0, \sigma^2)$. Note, that f_i consists of a smooth (e.g. spline) constructed via basis functions of different form and complexity, multiplied by a coeffecient:

$$f_i(x_i) \;=\; \sum_{k=1}^{K} \beta_{i,k} b_{i,k}(x_i). \tag{3}$$

Nested data structures (e.g. due to similar road [type]) can be accounted for by introducing random effects (Wood, 2017), while spatial dependence between observations can be included by constructing smoothing functions with e.g. northings and eastings, as for example done in (Augustin et al., 2009). Ultimately, the implementation of a such a GAMM will alow for establishing continuous prediction surfaces of growth potential (approximated via DBH) for individual species across urban areas (including parks) of Berlin.

Currently, DBH has been modelled using a hierarchical linear model (linear mixed effects model) with `lme4` (Bates et al., 2015) in R Core Team (2020). The general form of this model is:

$$Y_{i,j} = (\beta_0 + b_{0,i,j}) + (\beta_1 + b_{1,i,j}) \cdot x_i + \epsilon_{i,j}, \tag{4}$$

where β_0 is the intercept with its random component b_0, and β_1 the slope with its random component b_1. The random errors are assumed i.i.d. and distributed as $b \sim \mathcal{N}(0, \tau^2)$. The model for which results are presented in Figure 5 estimates DBH from tree age and the local UHI intensity as continuous covariates with random slopes and intercepts for each species; note, that for computational efficiency each genera was modelled seperately. Further, models were only established for species with at least 150 individuals.

2.2 Available and required data

Table 1 provides a list with currently accessible/available data, including information on (desired) resolution, and sources.

Table 1: Data requirements for analysis, including currently available/accessed and required/desired data.

Subject/Relevance	Desc.	Type	Obsv. (n)	Resolution (m)	Source
available or accessed					
urban trees	riparian, street, park; basic mensuration data (not for riparian)	tabular, spatial points	668254	NA	Senatsverwaltung Berlin
UHI Effect	raster data set with summer day/night time (global coverage; Berlin included)	raster	NA	200	UHI Explorer, [@chakraborty2019]
soil coverage (Baumscheibe)	available soil area and bounding infrastructure of trees	tabular, spatial polygons	178576	NA	Senatsverwaltung Berlin
vegetation and building height	data specific for indidivual building (complexes) and vegetation	tabular, spatial polygons	NA	NA	Senatsverwaltung Berlin
required and/or desired					
UHI Effect	raster data set with summer day/night time (global coverage; Berlin included)	raster	NA	< 50	? Landsat / Sentinel
road / street characteristics	orientation and width of streets	tabular	NA	NA	? Senatsverwaltung, urban planning
street tree density	planting density of trees as proxy for potential density-dependent inhibition	tabular or raster	NA	< 50	? Senatsverwaltung, urban planning
landcover data	providing local development intensity	tabular or raster	NA	100 - 200	? Landsat / Sentinel, Senatsverwaltung
tree growth series	*tree specific, incremental*	*tabular*	*NA*	*NA*	*? Field work, partners*

Table 2: Trees

Genera	**[0,30)**	**[30,60)**	**[60,90)**	**[90,120)**	**[120,150)**	**Total (n)**	**Missing (n)**
Tilia	41681	67565	38014	5571	213	163127	10083
Acer	31999	52798	15428	3160	219	140815	37211
Quercus	11473	20528	8981	4532	1030	64464	17920
Betula	6057	11178	2237	150	5	29013	9386
Platanus	5044	12618	5370	1811	861	26714	1010
Aesculus	5589	8717	6657	1850	209	25909	2887
Robinia	4469	9413	2365	401	31	24238	7559
Populus	1527	7794	3285	1130	222	19973	6015
Carpinus	6226	5274	1002	306	16	17951	5127
Prunus	6747	4033	362	44	5	17904	6713
Fraxinus	6098	4985	1178	261	22	16835	4291
Pinus	1990	3814	2060	368	21	14915	6662
Other	32888	22619	5885	3893	291	106396	40820
Marg. Totals	161788	231336	92824	23477	3145	668254	155684

3 Preliminary results

Tree locations are clustered and follow spatial structures based on their category, i.e. riparian, street and park trees (Fig. 1). Planting in space and time shows species specific patterns (by districts), often related to major events, such as the start and end of wars, as well as the German separation (not shown here). Table 2 shows the binned distribution of generae across age classes.

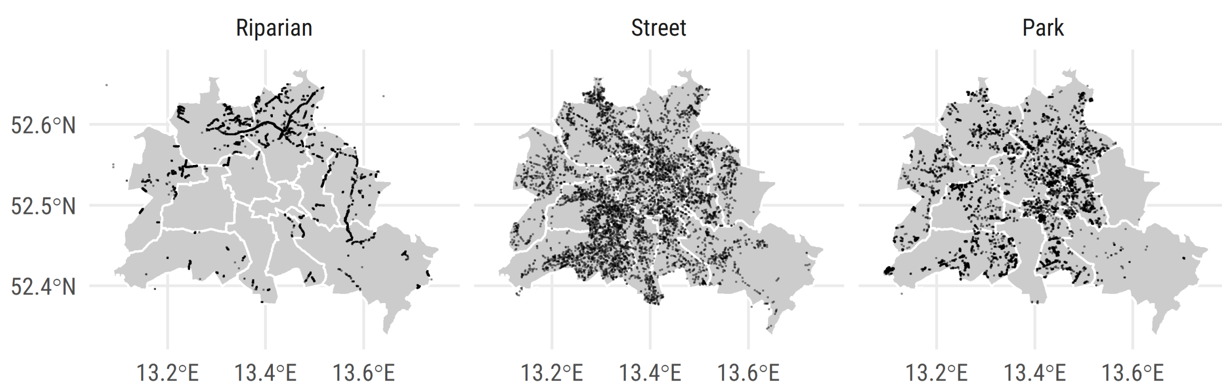

Figure 1: Individual tree locations for three categories available in Berlin Senate urban tree data set. Note, that for each category 7000 observations were subsampled from the available pool to facilitate visualization.

The distribution of the UHI effect is highly irregular and clustered in space (Fig. 3), and also shows variability through time (data not shown, refer to the urban heat island explorer).

The exposure to increased heat-loading of individual genera (and consequently species) is highly uneven throughout the city (Fig. 4). Street and park trees of most genera are clustered in urban areas with intermediate to high UHI loading, while riparian trees, and some street and park trees of other genera tend to be spread more evenly across Berlin's UHI range.

The effect of UHI loading on absolute growth potential varies between genera and species (Fig. 5). Most

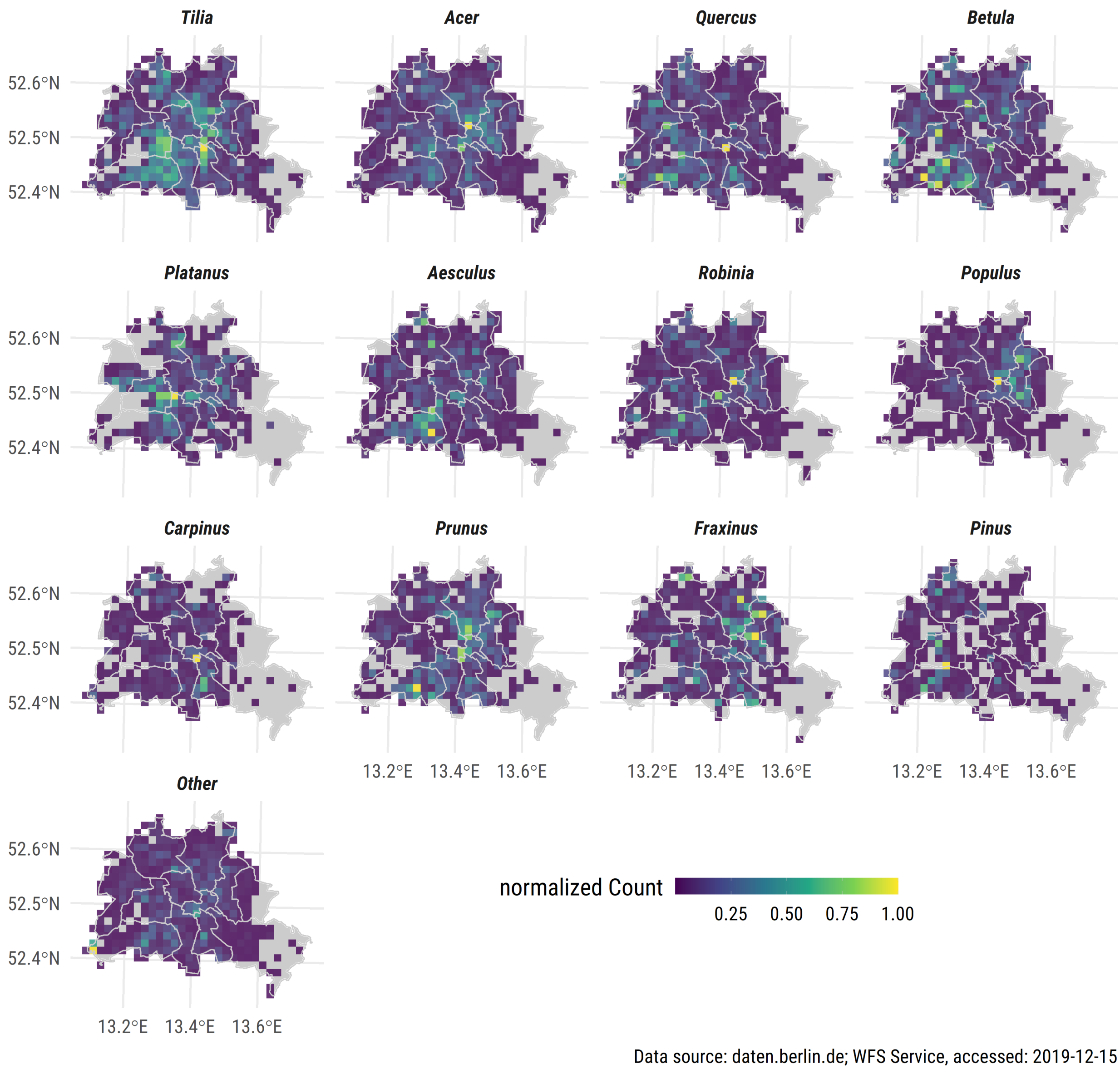

Figure 2: Gridded counts for the 11 most frequent genera, as well as *Pinus* and remaining genera. Note, that counts are standardized to unity for individual genera.

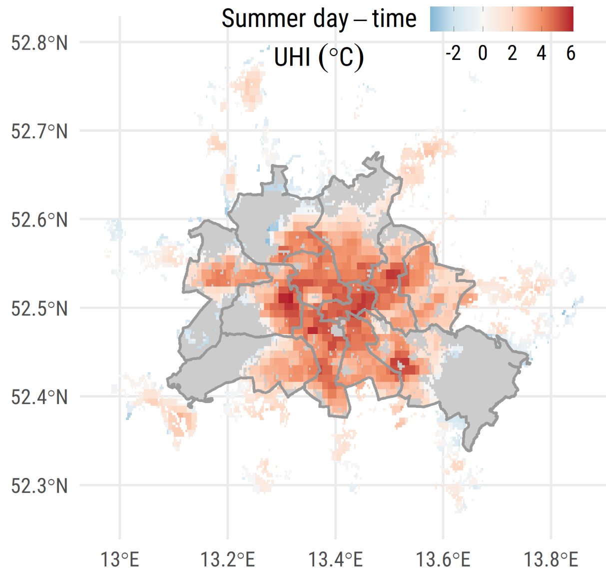

Figure 3: Estimate of UHI intensity based on the algorithm in (Chakraborty and Lee, 2019), comparing urban with rural pixels within the greater metropolitan cluster. Presented values are averaged over the summer of 2007.

notably, *Quercus*, the 3rd-most frequent genera, shows decreased absolute growth with increased UHI, while the most frequent genera, *Tilia* clearly features enhanced growth. Note, that the estimated effect sizes here are linear. Temperature may excert a non-linear control on absolute growth, however, and hence, applying a method able to capture may result in altered presented effect sizes. Additionally, if temperatures increase in the future under climate warming current future increases in under climate warming, any non-linear effects may become more enhanced, stressing the need for a more flexible model fit and structure.

alter the (preliminary) results substantially

Figure 5 shows how we can have a caption and cross-reference for a plot

4 Outlook

We seek to build upon and improve the current analysis by:

- incorporating more pertinent covariates as dependent variables in the linear mixed model
- testing multiple model structures with formal model selection procedures
- checking model resiudals for spatial auto-correlation and accounting for it where necessary to ensure unbiased estimates of effect sizes
- repeating the above with a hierarchical GAM (i.e. GAMM) to allow for:
  - estimating continuous prediction surfaces for UHI impacts on individual species' growth (similar to results in Figure 5) under recent conditions
  - estimating absolute, species-specific growth potential under increased temperatures and UHI loading under climate change, ideally based on climate simulations (otherwise step-wise increases based on RCP scenarios) for the key species. Note, that complications presented by 'out-of-sample' predictions will be addressed.
  - assess potential age-dependent UHI impacts on individual species.

5 Acknowledgements

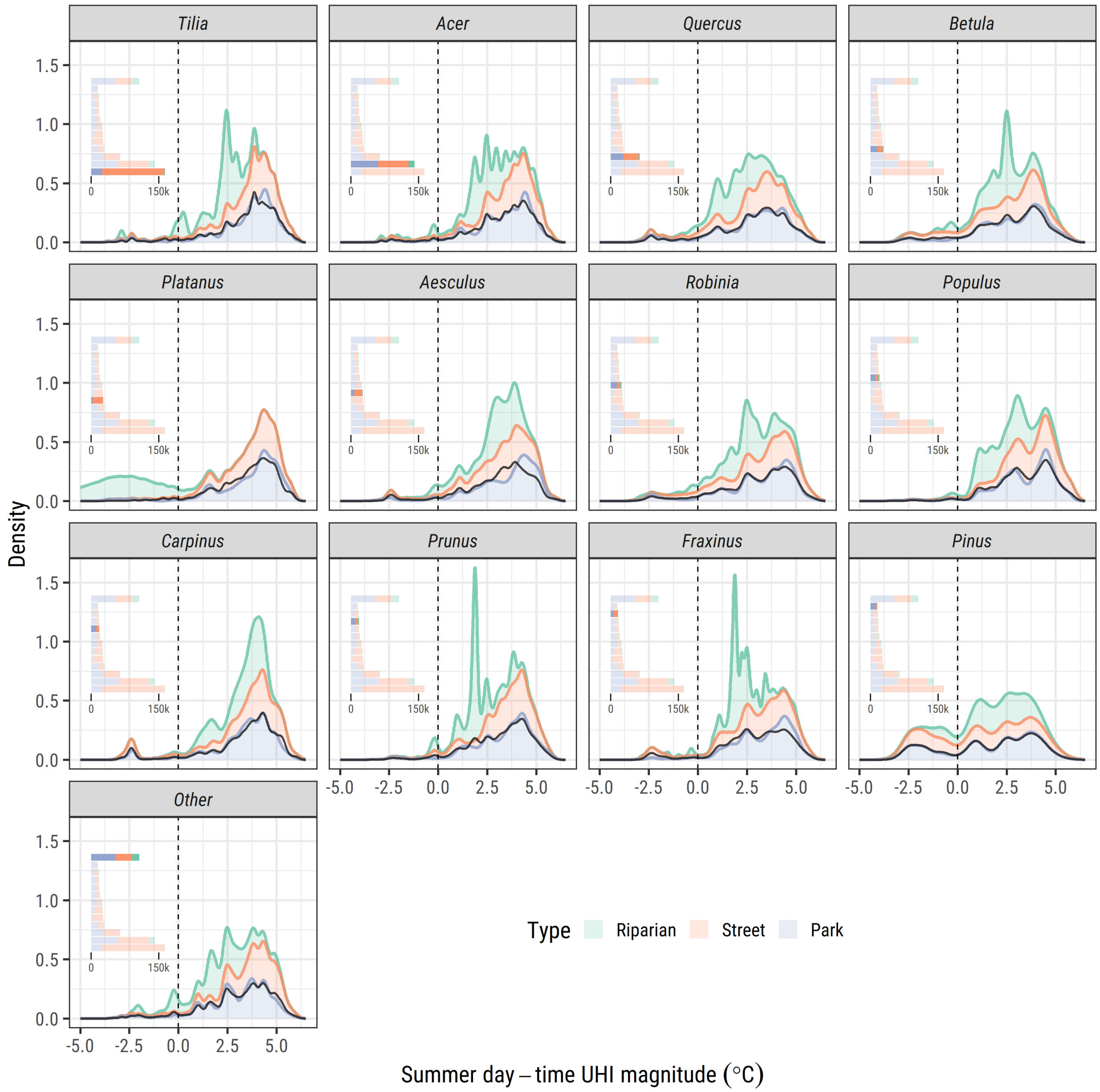

Figure 4: Empirical density distribution of all individuals within the presented genera along the UHI continuum. UHI intensities were extracted for each tree location, and the distribution hence represents the first detailed overview of the exposure of Berlin's trees to urban heat loading. The black line represents the density across all three categories. Insets represent corresponding tree totals.

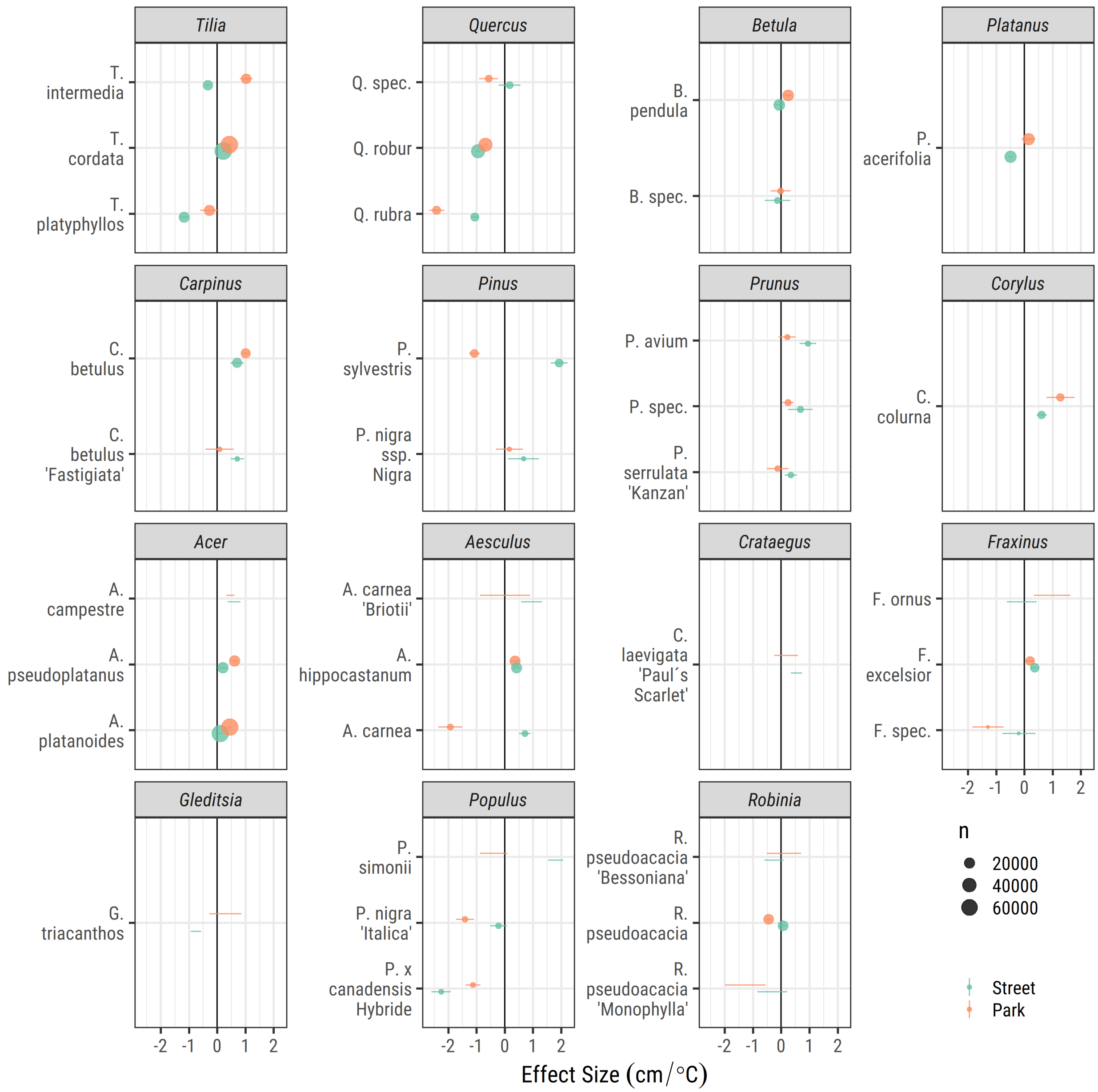

Figure 5: Impact of UHI loading on tree diameter (DBH), accounting for age and inter-specific differences from the linear mixed model (via random slopes and intercepts). Line-ranges are standard errors of predicted effect sizes (i.e. slopes). Differences between street and park trees are considerable for some species, and may be due to local clustering and/or spatial under-representation across the UHI continuum. Further investigations need to address the degree of spatial autocorrelation and account for it where required in linear mixed models, and with smoothing interactions in a GAMM implementation.

6 References

Akbari, H., Pomerantz, M., Taha, H., 2001. Cool surfaces and shade trees to reduce energy use and improve air quality in urban areas. Solar Energy, Urban Environment 70, 295–310. https://doi.org/10.1016/S0038-092X(00)00089-X

Augustin, N.H., Musio, M., von Wilpert, K., Kublin, E., Wood, S.N., Schumacher, M., 2009. Modeling Spatiotemporal Forest Health Monitoring Data. Journal of the American Statistical Association 104, 899–911. https://doi.org/10.1198/jasa.2009.ap07058

Bates, D., Mächler, M., Bolker, B., Walker, S., 2015. Fitting linear mixed-effects models using lme4. Journal of Statistical Software 67, 1–48. https://doi.org/10.18637/jss.v067.i01

Brune, M., 2016. Urban trees under climate change. Potential impacts of dry spells and heat waves in three German regions in the 2050s (No. Report 24). Climate Service Center Germany, Hamburg.

Chakraborty, T., Lee, X., 2019. A simplified urban-extent algorithm to characterize surface urban heat islands on a global scale and examine vegetation control on their spatiotemporal variability. International Journal of Applied Earth Observation and Geoinformation 74, 269–280. https://doi.org/10.1016/j.jag.2018.09.015

Dahlhausen, J., Rötzer, T., Biber, P., Uhl, E., Pretzsch, H., 2018. Urban climate modifies tree growth in Berlin. Int J Biometeorol 62, 795–808. https://doi.org/10.1007/s00484-017-1481-3

Endlicher, W., Scherer, D., Büter, B., Kuttler, W., Mathey, J., Schneider, C., 2016. Stadtnatur fördert gutes Stadtklima, in: Ökosystemleistungen in Der Stadt – Gesundheit Schützen Und Lebensqualität Erhöhen, 3.1. TEEB DE. TU Berlin, UFZ Leipzig, Berlin, Leipzig, pp. 51–63.

Fenner, D., Meier, F., Scherer, D., Polze, A., 2014. Spatial and temporal air temperature variability in Berlin, Germany, during the years 2001–2010. Urban Climate, ICUC8: The 8th International Conference on Urban Climate and the 10th Symposium on the Urban Environment 10, 308–331. https://doi.org/10.1016/j.uclim.2014.02.004

Gillner, S., Bräuning, A., Roloff, A., 2014. Dendrochronological analysis of urban trees: Climatic response and impact of drought on frequently used tree species. Trees 28, 1079–1093. https://doi.org/10.1007/s00468-014-1019-9

Gillner, S., Vogt, J., Tharang, A., Dettmann, S., Roloff, A., 2015. Role of street trees in mitigating effects of heat and drought at highly sealed urban sites. Landscape and Urban Planning 143, 33–42. https://doi.org/10.1016/j.landurbplan.2015.06.005

Grimmond, C., Souch, C., Hubble, M., 1996. Influence of tree cover on summertime surface energy balance fluxes, San Gabriel Valley, Los Angeles. Clim. Res. 6, 45–57. https://doi.org/10.3354/cr006045

Gulyás, Á., Unger, J., Matzarakis, A., 2006. Assessment of the microclimatic and human comfort conditions in a complex urban environment: Modelling and measurements. Building and Environment 41, 1713–1722. https://doi.org/10.1016/j.buildenv.2005.07.001

Hertel, D., Schlink, U., 2019. Decomposition of urban temperatures for targeted climate change adaptation. Environmental Modelling & Software 113, 20–28. https://doi.org/10.1016/j.envsoft.2018.11.015

Hoyano, A., 1988. Climatological uses of plants for solar control and the effects on the thermal environment of a building. Energy and Buildings 11, 181–199. https://doi.org/10.1016/0378-7788(88)90035-7

Jia, W., Zhao, S., Liu, S., 2018. Vegetation growth enhancement in urban environments of the Conterminous United States. Global Change Biology 24, 4084–4094. https://doi.org/10.1111/gcb.14317

Kuttler, W., Miethke, A., Dütemeyer, D., Barlag, A.-B. (Eds.), 2015. Das klima von essen = the climate of essen. Westarp Wiss., Hohenwarsleben.

Maras, I., Schmidt, T., Paas, B., Ziefle, M., Schneider, C., 2016. The impact of human-biometeorological factors on perceived thermal comfort in urban public places. https://doi.org/http://dx.doi.org/10.18452/18162

Mayer, H., Höppe, P., 1987. Thermal comfort of man in different urban environments. Theor Appl Climatol 38, 43–49. https://doi.org/10.1007/BF00866252

Moser-Reischl, A., Rahman, M.A., Pauleit, S., Pretzsch, H., Rötzer, T., 2019. Growth patterns and effects of urban micro-climate on two physiologically contrasting urban tree species. Landscape and Urban Planning 183, 88–99. https://doi.org/10.1016/j.landurbplan.2018.11.004

Norton, B.A., Coutts, A.M., Livesley, S.J., Harris, R.J., Hunter, A.M., Williams, N.S.G., 2015. Planning for cooler cities: A framework to prioritise green infrastructure to mitigate high temperatures in urban landscapes. Landscape and Urban Planning 134, 127–138. https://doi.org/10.1016/j.landurbplan.2014.10.018

Oke, T.R., 1982. The energetic basis of the urban heat island. Quarterly Journal of the Royal Meteorological Society 108, 1–24. https://doi.org/10.1002/qj.49710845502

Pauleit, S., Jones, N., Garcia-Martin, G., Garcia-Valdecantos, J.L., Rivière, L.M., Vidal-Beaudet, L., Bodson, M., Randrup, T.B., 2002. Tree establishment practice in towns and cities – Results from a European survey. Urban Forestry & Urban Greening 1, 83–96. https://doi.org/10.1078/1618-8667-00009

Pedersen, E.J., Miller, D.L., Simpson, G.L., Ross, N., 2019. Hierarchical generalized additive models in ecology: An introduction with mgcv. PeerJ 7, e6876. https://doi.org/10.7717/peerj.6876

Pretzsch, H., Biber, P., Uhl, E., Dahlhausen, J., Schütze, G., Perkins, D., Rötzer, T., Caldentey, J., Koike, T., Con, T. van, Chavanne, A., Toit, B. du, Foster, K., Lefer, B., 2017. Climate change accelerates growth of urban trees in metropolises worldwide. Scientific Reports 7, 1–10. https://doi.org/10.1038/s41598-017-14831-w

Quigley, M.F., 2004. Street trees and rural conspecifics: Will long-lived trees reach full size in urban conditions? Urban Ecosystems 7, 29–39. https://doi.org/10.1023/B:UECO.0000020170.58404.e9

Randrup, T.B., McPherson, E.G., Costello, L.R., 2001. A review of tree root conflicts with sidewalks, curbs, and roads. Urban Ecosystems 5, 209–225. https://doi.org/10.1023/A:1024046004731

R Core Team, 2020. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Rhoades, R.W., Stipes, R.J., 1999. Growth of trees on the Virgina Tech Campus in response to various factors 7.

Roloff, A., Korn, S., Gillner, S., 2009. The Climate-Species-Matrix to select tree species for urban habitats considering climate change. Urban Forestry & Urban Greening 8, 295–308. https://doi.org/10.1016/j.ufug.2009.08.002

Tzoulas, K., Korpela, K., Venn, S., Yli-Pelkonen, V., Kaźmierczak, A., Niemela, J., James, P., 2007. Promoting ecosystem and human health in urban areas using Green Infrastructure: A literature review. Landscape and Urban Planning 81, 167–178. https://doi.org/10.1016/j.landurbplan.2007.02.001

Wood, S.N., 2017. Generalized additive models: An introduction with R. CRC press.

Zhao, S., Liu, S., Zhou, D., 2016. Prevalent vegetation growth enhancement in urban environment. PNAS 113, 6313–6318. https://doi.org/10.1073/pnas.1602312113

6.0.1 Colophon

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#>  igraph        1.2.4.2   2019-11-27 [1] CRAN (R 3.6.2)
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#>  kableExtra  * 1.1.0     2019-03-16 [1] CRAN (R 3.6.3)
#>  KernSmooth    2.23-16   2019-10-15 [1] CRAN (R 3.6.3)
#>  knitr         1.28      2020-02-06 [1] CRAN (R 3.6.2)
#>  lattice       0.20-38   2018-11-04 [1] CRAN (R 3.6.3)
#>  lifecycle     0.2.0     2020-03-06 [1] CRAN (R 3.6.3)
#>  listenv       0.8.0     2019-12-05 [1] CRAN (R 3.6.2)
#>  lme4          1.1-21    2019-03-05 [1] CRAN (R 3.6.2)
#>  magrittr      1.5       2014-11-22 [1] CRAN (R 3.6.2)
#>  MASS          7.3-51.5  2019-12-20 [1] CRAN (R 3.6.3)
#>  Matrix        1.2-18    2019-11-27 [1] CRAN (R 3.6.3)
#>  memoise       1.1.0     2017-04-21 [1] CRAN (R 3.6.2)
#>  minqa         1.2.4     2014-10-09 [1] CRAN (R 3.6.2)
#>  munsell       0.5.0     2018-06-12 [1] CRAN (R 3.6.2)
#>  nlme          3.1-144   2020-02-06 [1] CRAN (R 3.6.3)
#>  nloptr        1.2.2     2020-02-29 [1] CRAN (R 3.6.3)
#>  pillar        1.4.3     2019-12-20 [1] CRAN (R 3.6.2)
#>  pkgbuild      1.0.6     2019-10-09 [1] CRAN (R 3.6.2)
#>  pkgconfig     2.0.3     2019-09-22 [1] CRAN (R 3.6.2)
#>  pkgload       1.0.2     2018-10-29 [1] CRAN (R 3.6.2)
#>  prettyunits   1.1.1     2020-01-24 [1] CRAN (R 3.6.2)
#>  processx      3.4.2     2020-02-09 [1] CRAN (R 3.6.2)
#>  progress      1.2.2     2019-05-16 [1] CRAN (R 3.6.3)
#>  ps            1.3.2     2020-02-13 [1] CRAN (R 3.6.2)
#>  purrr         0.3.3     2019-10-18 [1] CRAN (R 3.6.2)
#>  R6            2.4.1     2019-11-12 [1] CRAN (R 3.6.2)
#>  raster        3.0-12    2020-01-30 [1] CRAN (R 3.6.3)
#>  Rcpp          1.0.3     2019-11-08 [1] CRAN (R 3.6.2)
#>  readr         1.3.1     2018-12-21 [1] CRAN (R 3.6.3)
#>  remotes       2.1.1     2020-02-15 [1] CRAN (R 3.6.2)
#>  rlang         0.4.5     2020-03-01 [1] CRAN (R 3.6.3)
#>  rmarkdown     2.1       2020-01-20 [1] CRAN (R 3.6.2)
#>  rprojroot     1.3-2     2018-01-03 [1] CRAN (R 3.6.2)
#>  rstudioapi    0.11      2020-02-07 [1] CRAN (R 3.6.2)
#>  rvest         0.3.5     2019-11-08 [1] CRAN (R 3.6.3)
#>  scales        1.1.0     2019-11-18 [1] CRAN (R 3.6.2)
#>  sessioninfo   1.1.1     2018-11-05 [1] CRAN (R 3.6.2)
#>  sf            0.8-1     2020-01-28 [1] CRAN (R 3.6.2)
#>  sp            1.4-1     2020-02-28 [1] CRAN (R 3.6.3)
#>  storr         1.2.1     2018-10-18 [1] CRAN (R 3.6.2)
#>  stringi       1.4.6     2020-02-17 [1] CRAN (R 3.6.2)
#>  stringr       1.4.0     2019-02-10 [1] CRAN (R 3.6.2)
#>  testthat      2.3.2     2020-03-02 [1] CRAN (R 3.6.3)
#>  tibble        2.1.3     2019-06-06 [1] CRAN (R 3.6.2)
#>  tidyselect  * 1.0.0     2020-01-27 [1] CRAN (R 3.6.2)
#>  txtq          0.2.0     2019-10-15 [1] CRAN (R 3.6.2)
#>  units         0.6-5     2019-10-08 [1] CRAN (R 3.6.2)
#>  usethis       1.5.1     2019-07-04 [1] CRAN (R 3.6.2)
#>  vctrs         0.2.4     2020-03-10 [1] CRAN (R 3.6.3)
#>  viridisLite   0.3.0     2018-02-01 [1] CRAN (R 3.6.2)
```

```
#>  webshot        0.5.2      2019-11-22 [1] CRAN (R 3.6.3)
#>  withr          2.1.2      2018-03-15 [1] CRAN (R 3.6.2)
#>  xfun           0.12       2020-01-13 [1] CRAN (R 3.6.2)
#>  xml2           1.2.5      2020-03-11 [1] CRAN (R 3.6.3)
#>  yaml           2.2.1      2020-02-01 [1] CRAN (R 3.6.2)
#>
#> [1] C:/Program Files/R/R-3.6.3/library
```

The current Git commit details are:

```
#> Local:    master C:/Users/ahurl/Documents/_work/p024_gfz_berlin-trees/berlin.trees
#> Remote:   master @ origin (https://github.com/the-Hull/berlin.trees.git)
#> Head:     [3fcb46e] 2020-03-09: updated methods brief
```