



1 **When trees don't act their age: size-deterministic tree-ring**
2 **standardization for long-term trend estimation in shade-tolerant**
3 **trees**

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15 **Abstract**

16 With increasing awareness of the consequences of climate change for global ecosystems, the
17 focus and application of tree-ring research has shifted to reconstruction of long-term climate-
18 related trends in tree growth. Contemporary methods for removing the biological growth-trend
19 from tree-ring series (standardization) are ill-adapted to shade-tolerant species, leading to biases
20 in the resultant chronology. Further, many methods, including regional curve standardization
21 (RCS), encounter significant limitations for species in which accurate age estimation is difficult.
22 In this study we present and test two tree-ring standardization models that integrate tree size in
23 the year of ring formation into the estimation of the biological growth-trend. The first method,
24 dubbed size deterministic standardization (SDS), uses tree diameter as the sole predictor of the
25 growth-trend. The second method includes the combined (COMB) effects of age and diameter.
26 We show that both the SDS and COMB methods reproduce long-term trends in simulated tree-
27 ring data better than conventional methods – this result is consistent across multiple species.
28 Further, when applied to real tree-ring data, the COMB method is more parsimonious than its
29 than RCS. We recommend the inclusion of tree size in the year of ring formation in future tree-
30 ring standardization models, particularly when dealing with shade-tolerant species, as it does not
31 compromise model parsimony and allows for the inclusion of unaged trees.

32 **1 Introduction**

33 Tree-rings have long-served as a record of environmental change in forest ecosystems. Early
34 dendrochronological studies used tree-ring chronologies from climate sensitive species to
35 elucidate the dynamics of growth-climate relationships and reconstruct climate anomalies from
36 periods before the existence of instrumental records. However, with increasing awareness of the
37 consequences of climate change for global ecosystems, the focus and application of tree-ring



38 research has shifted to reconstruction of low-frequency climate related trends in tree growth
39 (Gedalof and Berg 2010, Boisvenue and Running 2006, Jacoby and D'Arrigo 1997). As it stands,
40 previous optimism regarding the benefits of carbon fertilization for forest growth (Battipaglia et
41 al. 2012, Norby et al. 2005) has been quelled by a lack of consistent evidence in real forests.
42 While many studies have noted increases in long-term growth rates over time in temperate
43 forests (Gedalof and Berg 2010, Huang et al. 2007, Martinelli 2004) others suggest no change
44 (Giguère-Croteau et al. 2019, Camarero et al. 2015, Granda et al. 2014, Silva et al. 2010,
45 Peñuelas et al. 2011). Further, in boreal and drought prone species, growth decline (Chen et al.
46 2017, Dietrich et al. 2016, Girardin et al. 2012, Silva and Anand 2013) and increased mortality
47 (Herguido et al. 2016, Liang et al. 2016) in response to climate stress have been prevalent.
48 Central to all these studies is the assumption that long-term growth-trends can be accurately and
49 unbiasedly estimated from tree-ring data.

50 As it stands, accurate estimation of long-term growth-trends in forests may be limited by poorly
51 adapted tree-ring standardization (age-trend removal) methods (Briffa et al. 1996) and
52 inappropriate sampling methods (Nehrbass-Ahles et al. 2014, Brien et al. 2012). Early
53 standardization methods (i.e. conservative detrending) were designed to maintain high-frequency
54 variation in tree-ring series and discard long-term, low-frequency variation. It is accepted that
55 these methods are inappropriate for estimating long-term climate related growth-trends (Briffa
56 1992); however, they are still used in situations where contemporary standardization methods are
57 not applicable due to restrictive data requirements (e.g. Villalba et al. 2012, Gedalof and Berg
58 2010, Geoff Wang et al. 2006). More recently, the use of regional curve standardization (RCS),
59 and its many variants, as well as the conversion of tree-ring widths to basal area increments
60 (BAI) have become commonplace (Peters et al. 2015). But, due to the difficulties in separating

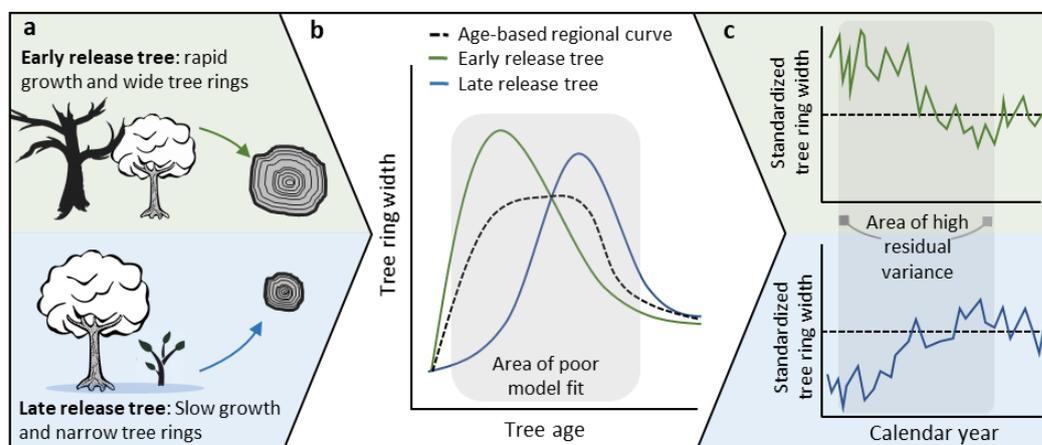


61 climate related trends that vary on long time scales from those related to biological tree growth
62 and/or succession-related environmental change, neither of these methods are likely to produce
63 accurate estimates of external forcing when trees from only a single age/size class are sampled
64 (Brienen et al. 2012, Briffa and Melvin 2011). While increased awareness of sample biases has
65 led to better prescriptions for study design (see Nehrbass-Ahles et al. 2014, Brienen et al. 2012),
66 systematic tests of the ability of these models to accurately reproduce long-term trends are
67 limited (e.g. Sullivan et al. 2016, Peters et al. 2015, Esper 2010).

68 RCS remains the standard method for estimating long-term growth-trends in tree-ring data
69 (Helama et al. 2017). However, the standard RCS approach encounters large limitations for
70 many species in which accurate age estimation is difficult. Additionally, we suggest the inherent
71 assumption of RCS that biological growth-trends are sufficiently determined by tree age may not
72 be appropriate in all species. More specifically, this assumption is problematic for shade-tolerant
73 trees. Shade-tolerant species exhibit relatively low low-light mortality and thus can persist in
74 forest understories for variable amounts of time before release from overstory light suppression.
75 In these cases, traditional age-deterministic models exhibit high variance, and thus low precision,
76 in the period following tree establishment and leading up to the age when most trees have been
77 released from suppression (Fig. 1). This period of ill-fit means that trees which are released
78 relatively early (or late) from light suppression will exhibit inflated (or deflated) growth relative
79 to the chronology. As a result, the final chronology will show less agreement than would be
80 expected in a shade-intolerant species. Even more problematic, if trees are sampled according to
81 minimum size thresholds, the youngest trees in the chronology are likely to be early-release trees
82 leading to an artificial inflation of modern growth rates in the final chronology. While
83 modifications to traditional RCS that address variance in contemporaneous growth rates and



84 regional environmental conditions have been prevalent in shade-intolerant species (see Helama
85 et al. 2017) there has been little to no focus on the improvement of standardization techniques
86 specific to shade-tolerant tree species.



87 **Figure 1: (a) In shade-tolerant species young trees are stochastically released from low-light suppression in**
88 **the understory. (b) Since release from suppression is not strictly related to tree age, widely used communal**
89 **age-trend models (RCS) poorly model tree growth in the period following establishment and leading up to the**
90 **age when most trees have been released from suppression. (c) Poor model-fit in this period implies that the**
91 **biological growth-trend is not entirely removed from individual series and leads to high residual variance**
92 **when standardized tree-ring series are aligned according to calendar year.**

93 Alternatively, in the field of forest growth and yield modelling, size, rather than age,
94 deterministic predictive growth models are ubiquitous. It is well understood that tree size
95 regulates the capacity for resource acquisition, namely, light (Canham et al. 2004), water and
96 nutrients (Homann et al. 2000), resource allocation (Lehnebach et al. 2018) and metabolic costs
97 (West et al. 2001). As such, the notion of radial growth being deterministic according to size
98 rather than age is logical from both a physiological and ecological perspective. We propose that a
99 size-deterministic model for tree-ring standardization may be more appropriate than traditional
100 RCS for shade-tolerant tree species. The application of size-deterministic models has been
101 limited, with few examples of tree size in a given year being incorporated into BAI models (e.g.
102 Marqués et al. 2016, Camarero et al. 2015, Nock et al. 2011, Martínez-Vilalta et al. 2008) and
103 even fewer of uniquely size-based tree-ring models (e.g. Bontemps and Esper 2011). Further,



104 there have been no systematic evaluations of the ability of size-based models to accurately
105 estimate long-term trends in tree-ring series.

106 We present two tree-ring standardization models that integrate tree size in the year of ring
107 formation into estimation of the biological growth-trend. The first model uses tree diameter as
108 the sole predictor of the communal growth-trend while the second includes the combined effects
109 of both age and diameter. It follows that the objective of this study is to determine the efficacy of
110 both models in estimating long-term growth-trends in their resultant tree-ring chronologies. First,
111 we use modelled tree-ring data from shade-tolerant and intolerant species to make explicit the
112 inappropriateness of age-based models for shade-tolerant trees. Further, we investigate the
113 performance of size-based models relative to contemporary standardization methods in the
114 presence of size thresholds in tree sampling. Last, we apply the developed models to tree-ring
115 data from shade-tolerant temperate species to evaluate model performance relative to
116 contemporary methods on the basis of model-fit and chronology quality statistics.

117 **2 Methods**

118 **2.1 Model formulation**

119 Traditional RCS makes two assumptions about tree growth. First that trees of the same species in
120 a given region exhibit a common growth-trend as they age, and second, that growth of an
121 individual tree in a given year is thus a product of its age and common climatic or environmental
122 forcing in that year (Esper et al. 2003, Briffa et al. 1992). We present a variant of the RCS
123 method that uses tree size, measured by diameter at breast height (DBH), in the year of ring
124 formation as the primary determinant of the common biological growth-trend. As with RCS we
125 assume that the relationship between expected growth and tree size is non-linear and can be
126 approximated for a region from a sufficiently large sample of trees from the species in question.



127 Further, we assume that using a sample of trees from a range of size/age classes ensures
128 estimation of the common trend is not confounded by underlying low-frequency climate or
129 environmental forcing in the chronology (Brienen et al. 2012). The size-based regional curve
130 model, hereafter referred to as the **size deterministic standardization (SDS)** model, takes the
131 following form:

$$132 \quad (1) \ E(RW_{y,i}) = B_o + f_l(DBH_{y,i}) + e_{yi}$$

133 Where $E(RW_{y,i})$ represents the expected ring width of a given tree (i) in year (y), and f_l
134 represents a non-linear function relating DBH of a given tree (i) in year (y) to $E(RW_{y,i})$. The non-
135 linear relationship is estimated using penalized spline fitting techniques in a generalized additive
136 model (GAM). Under this paradigm the model residuals (e_{yi}) represent individual standardized
137 ring width indices and, by extension, individual tree response to climatic or environmental
138 forcing. Annual model residuals subject to a robust mean, thus, represent the final standardized
139 chronology. This approach differs slightly from traditional RCS, whereby occasionally
140 standardized ring width indices are produced by division of raw data by the expected value.
141 Calculation of standardized ring width indices by subtraction from the expected value, as in the
142 case of residuals, is now commonly used as it tends to reduce bias in the resultant chronology
143 (Helama et al. 2004) and eases in the formulation of more complex tree-ring standardization
144 models. However, unlike division methods, the subtraction method does not provide any
145 stabilization of variance in the resulting residuals; as such, it may be necessary to use a
146 stabilization procedure (i.e. log transformation, power transformation) on raw ring width data
147 beforehand.

148 Tree size in a given year can be estimated by outside-in or inside-out techniques. If the pith of a
149 tree is present in the core (or reasonably close to) DBH_y is a simple summation of all previous



150 ring widths since the year of origin, multiplied by two. Alternatively, if the pith is missed, DBH_y
151 can be calculated via subtraction of more modern ring widths (multiplied by two) from the
152 inside-bark diameter. In this case inside-bark diameter is calculated as the measured DBH minus
153 bark thickness (multiplied by two), where bark thickness can be directly measured or estimated
154 using species-specific allometric equations (e.g. Stayton and Hoffman 1970).

155 Similar to the model formulation for SDS, RCS models were estimated with GAMs of the
156 following form:

$$157 \quad (2) \ E(RW_{yi}) = B_o + f_1(\text{Age}_{yi}) + e_{yi}$$

158 Where Age_{yi} is the age of an individual tree in a given year and the resultant standardized tree-
159 ring indices are derived from model residuals (e_{yi}).

160 In addition, a more complex model that integrated independent size and age effects was also
161 evaluated for comparison. This model, hereafter referred to as the **combined model (COMB)**,
162 took the following form:

$$163 \quad (3) \ E(RW_{yi}) = B_o + f_1(\text{Age}_{yia}) + f_2(\text{DBH}_{yi}) + e_{iy}$$

164 In a large variety of long-lived tree species, accurate age estimation (pith sampling) is difficult or
165 impossible; rendering traditional RCS or combined models inappropriate for all trees sampled.

166 To address this issue, the above model incorporates unaged trees. Here f_1 represents the non-
167 linear function relating age to expected ring width for the subset of all trees that are aged (ia). In
168 this model, ring widths from unaged trees are assigned arbitrary ages which do not contribute to
169 the linear approximation of the smooth term for Age (i.e. $f_1(\text{Age}_{yia})$) but these trees still contribute
170 to the smooth term for size $f_2(\text{DBH}_{yi})$. Syntax for missing data in GAMs followed the protocol



171 provided in mgcv (Wood 2011). In this study all GAMs were fit using the mgcv package (Wood
172 2011) in the R statistical program (v.3.5.0).

173 In addition to the models presented above we investigated two more contemporary
174 standardization methods; conservative detrending (CD) and BAI. Conservative detrending
175 describes functions (i.e. negative exponentials, straight lines) or flexible splines fit to individual
176 tree-ring series. In this study we use spline fitting techniques rather than modified negative
177 exponentials as they are more appropriate for shade-tolerant tree species. Alternatively, BAI
178 attempts to remove biological growth-trends by converting ring widths from individual trees to
179 estimates of annual basal area growth. For simplicity, untransformed BAI was used to compile
180 chronologies for this study. Both CD and BAI methods were applied using the dplR package
181 (Bunn 2008) in R.

182 **2.2 Simulated tree-ring data**

183 To evaluate the efficacy of each standardization method in detecting long-term trends, we
184 simulated tree-ring data using a well-established gap-phase model. The SORTIE-ND model was
185 chosen over other similar gap-phase models as it better emulates understory light conditions and
186 low-light mortality both of which are central to the notion of age being an inappropriate
187 determinant of growth in shade-tolerant species. For simplicity, a 100% sugar maple (*Acer*
188 *saccharum*) dominated stand was simulated as sugar maple is a model shade-tolerant species that
189 grows in self-replacing stands. All living trees (>5 cm dbh), (n=3657) in the final year of the
190 model run were used for further analysis. Additionally, to elucidate our claim that age-
191 deterministic growth estimation is more problematic in shade-tolerant species, we completed a
192 similar SORTIE simulation for the shade-intolerant species white pine (*Pinus strobus*). Again,
193 the stand was 100% white pine, standard model parameters were used, and the simulation was



194 run for 1000 years. All living trees (>5 cm dbh), (n=7362) in the final year of the model run were
195 used for further analysis. Additional details regarding model parameters for the SORTIE
196 simulations are provided in the supplementary materials (Suppl. S1).

197 To simulate a low-frequency climate related growth-trend, a logistic trend was added to raw tree-
198 ring width of individual trees produced by both SORTIE simulations. The logistic trend
199 simulated an initial rapid increase in growth and subsequent levelling off that aimed to represent
200 a period of carbon fertilization and eventual acclimation. The logistic model was applied to the
201 last 100 years of growth and took the following form, where RW_t represents ring widths with the
202 simulated long-term trend and RW_r are raw ring widths:

$$203 \quad (4) \quad RW_{t_{yi}} = RW_{r_{yi}} + \frac{0.6 * \overline{RW}_i}{1 + ae^{-r * y}}$$

204 The logistic trend parameters (r , a) were chosen such that increases in growth did not exceed 5%
205 of individual average tree growth per decade.

206 Sixty trees were randomly selected, without replacement, from the simulated tree populations
207 and subject to each of the five standardization methods (SDS, RCS, COMB, CD, BAI). Model
208 residuals (in the case of RCS, SDS and COMB), and standardized (CD) or transformed (BAI)
209 tree-ring widths were compiled into an annual mean chronology using Tukey's biweight robust
210 mean. The resultant chronologies were then tested for significant correlation with the logistic
211 growth-trend using Spearman's rank correlation coefficient. This process was bootstrap
212 resampled 100 times to produce confidence intervals for correlation coefficients.

213 To examine the effect of minimum size sampling thresholds on the accuracy of long-term trend
214 reconstruction by each of the standardization methods, we completed the same analysis on trees
215 from the simulated populations that exceeded certain size thresholds. The thresholds employed



216 were 10 cm DBH, which represented a practical minimum size threshold for sampling, and 30
217 and 50 cm DBH which represented thresholds for mature and dominant trees, respectively. The
218 mean Spearman's rho for all detrending methods and sampling thresholds were compared using
219 two-way ANOVA and post-hoc tests. Further, two-way ANOVA compared the effect of model
220 choice on Spearman's rho between species (sugar maple and white pine).

221 **2.3 Real tree-ring data**

222 We evaluated the appropriateness of the SDS, COMB and RCS models for use in real tree-ring
223 data from shade-tolerant species. We collected tree-ring data from seven mature sugar maple
224 dominated stands in Ontario, Canada (Table 1). Further, tree-ring data sets from the shade-
225 tolerant species red spruce (*Picea rubens*) were obtained from the DendroEcological Network
226 database (<https://www.uvm.edu/femc/dendro>), (Table 1). Red spruce was chosen as it had
227 sufficient replication across studies in the database. Descriptions of the sampling strategies and
228 data processing methods for all sites considered are provided in either the supplementary
229 materials (Suppl. S2) or in their respective references (i.e. Kosiba 2013, Kosiba 2017). Data was
230 considered suitable for this study if age and DBH estimates were provided and if a minimum 20
231 trees per site and species were sampled. All cores in which pith offset was estimated to be greater
232 than 10 years were considered unaged. The SDS, RCS, and COMB models were fit to tree-ring
233 data from all site-species combinations and the resultant chronologies were compiled with a
234 robust mean. In all cases models were fit to log-transformed ring widths, as it increased residual



235 homoskedasticity. For simplicity and ease of model comparison we did not fit CD or BAI models
 236 to the real tree-ring data set.

237 Model fits from the SDS, RCS and COMB methods were compared according to Akaike
 238 information criterion (AIC) and percent variance explained (R^2). Since model comparison via
 239 AIC requires equal sample sizes, reduced data SDS (SDS_{red}) and COMB ($COMB_{red}$) models,
 240 which only included aged trees, were also fit. These reduced data models have no practical
 241 application but allow for direct AIC comparison between the RCS, $COMB_{red}$ and SDS_{red} models.

Table 1:

Location, sample size, chronology length and source of tree ring data sets used in this study.

Species	Site (code)	Longitude (°)	Latitude (°)	N. trees total	N. trees aged	Length of chronology	Source
Sugar maple (<i>A. saccharum</i>)	Toobee Lake (TB)	46.7459	-82.8668	79	67	1750-2015	This study
	Wolf Mtn. (WM)	46.7390	-82.8467	22	18	1827-2015	...
	Roosevelt Road (RS)	47.2852	-79.7063	20	11	1792-2016	...
	Raven Lake (RL)	45.3309	-78.6339	31	19	1864-2015	...
	Freezy Lake (FR)	45.2998	-78.4329	20	11	1887-2015	...
	Kakakise Lake (KK)	46.0554	-81.3317	22	7	1773-2016	...
	Mt. Zion Road (MT)	46.4000	-83.7004	29	15	1777-2015	...
Red spruce (<i>P. rubens</i>)	Mt. Mansfield (MTM)	44.3750	-73.8750	111	109	1769-2011	Kosiba et al. (2016)
	Burnt Mtn. (BNT)	44.2068	-72.3515	40	40	1891-2010	Kosiba et al. (2013)
	Mt. Carmel (CAR)	43.7709	-72.9205	41	41	1795-2010	...
	Mt. Ellen (ELL)	44.1656	-72.9221	42	42	1824-2010	...
	Mt. Equinox (EQU)	43.1487	-73.1273	89	89	1857-2010	...
	Mt. Greylock (GRY)	42.6738	-73.1575	44	44	1911-2010	...
	Hubbard Brook (HUB)	43.9577	-71.7350	89	89	1885-2010	...
	Killington Mtn. (KIL)	43.6146	-72.8088	104	103	1742-2010	...
	Mt. Mansfield (MAN)	44.5106	-72.8297	57	57	1767-2010	...
	Mt. Moosilauke (MOO)	44.0056	-71.8215	54	54	1760-2010	...
Mad River Glen (MRG)	44.1932	-72.9232	36	36	1927-2010	...	

242 Further, we calculated chronology quality statistics including: mean interseries-correlation,
 243 expressed population signal (EPS) and signal-to-noise ratio (SNR), for all chronologies.



244 Differences between model fit statistics and quality indices among models were tested using a
245 linear mixed-effect modelling (LME) approach whereby, model error was specified according to
246 site. This approach is analogous to traditional repeated-measures ANOVA but allows for contrast
247 analysis between models.

248 **3 Results**

249 **3.1 Comparisons of methods in simulated data**

250 Bootstrapped correlations for chronologies produced by each standardization method are
251 displayed in Figure 2a for the sugar maple and Figure 2b for white pine.

252 The sugar maple two-way ANOVA suggested a significant effect of both standardization model
253 ($p < 0.001$) and minimum size sampling threshold ($p < 0.001$) on average correlation. Across all
254 sampling thresholds the SDS model produced chronologies with the highest mean correlation
255 ($\bar{r}_s = 0.972 \pm 0.024$). Tukey HSD contrasts suggested mean correlation for the SDS model was
256 significantly higher than all other models ($p < 0.001$, all cases) except for the COMB model
257 ($\bar{r}_s = 0.969 \pm 0.023$), ($p = 0.993$) which produced the second highest mean correlation. BAI produced
258 the third highest mean correlation ($\bar{r}_s = 0.954 \pm 0.103$) which was not significantly different from
259 the combined model ($p = 0.61$) but was significantly higher than correlations from the two
260 remaining models (RCS and CD), ($p < 0.001$). The CD ($\bar{r}_s = 0.720 \pm 0.153$) and RCS
261 ($\bar{r}_s = 0.925 \pm 0.054$) models produced the lowest and second lowest correlations respectively; both
262 were significantly different from each other and all other models ($p < 0.01$, all cases).

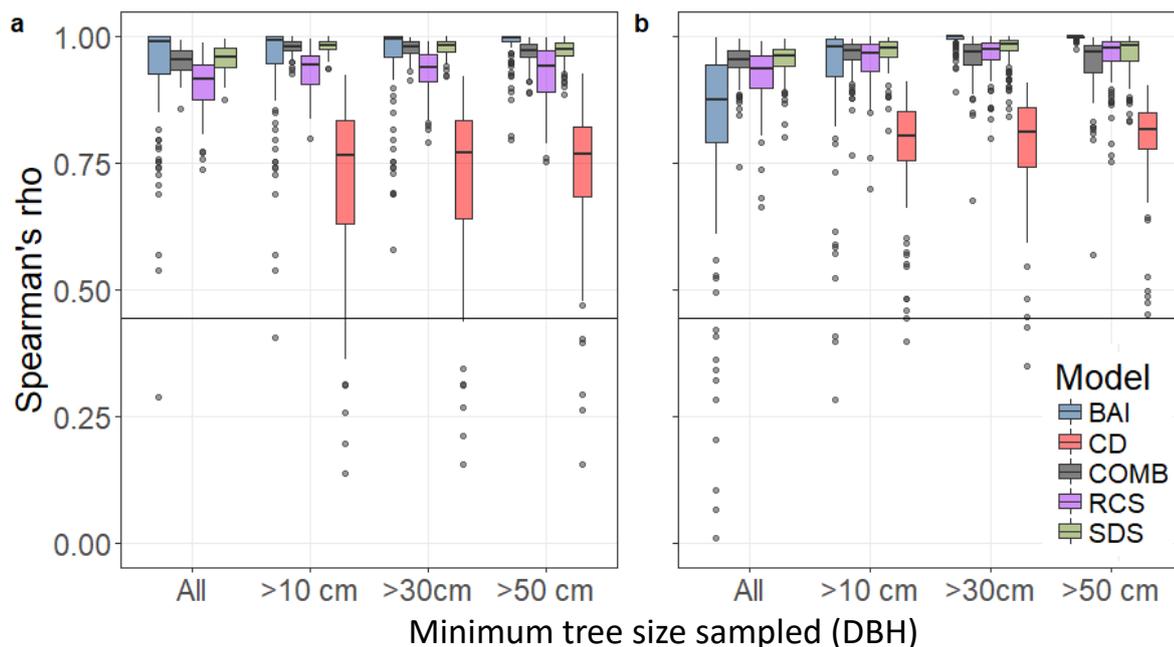


Figure 2: Spearman's rank correlation between chronologies produced by each of the five standardization methods and the imposed logistical trend in simulated (a) sugar maple and (b) white pine tree-ring data. Horizontal axis denotes minimum tree size (DBH) thresholds for sampling from the population.

263 Contrasts suggested that the significant effect of minimum size threshold was driven by
264 significant differences in correlations between BAI produced chronologies among samples. As
265 evident in Figure 2a, BAI chronologies performed best when size thresholds exceeded 50 cm
266 DBH. At this threshold BAI chronologies produced significantly higher correlations than when
267 all trees were sampled ($p=0.002$) and marginally significantly higher correlations than when trees
268 >10 cm DBH were sampled ($p=0.054$). Contrastingly, the SDS, RCS, COMB and CD
269 chronologies produced similar correlations across all minimum size thresholds. Bootstrapped
270 sugar maple chronologies produced by each of the standardization methods are provided in
271 Figure 3a.

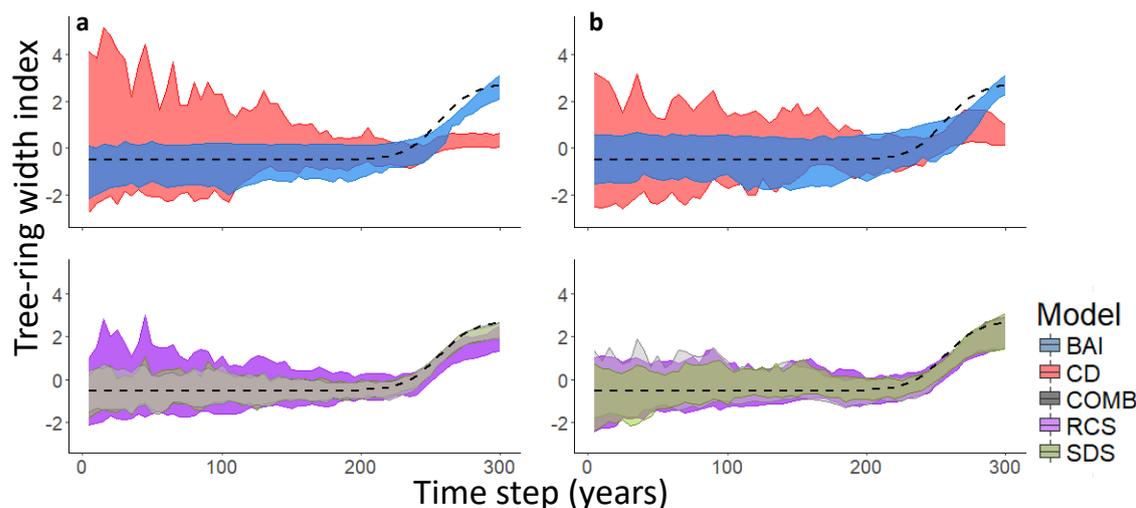


Figure 3: 95% confidence intervals for chronologies produced by each standardization method in SORTIE simulated (a) sugar maple and (b) white pine tree-ring data (Top: BAI, CD; Bottom: SDS, RCS, COMB). Confidence intervals were obtained via bootstrap resampling (rep=100) of 60 trees (>10 cm DBH) from the SORTIE simulated populations. Dotted lines indicate the logistic trend that was added to the raw tree-ring data. For ease of comparison all chronologies and the simulated trend were centred and scaled before plotting.

272 The white pine two-way ANOVA also suggested a significant effect of both standardization
273 model ($p < 0.001$) and minimum size sampling threshold ($p < 0.001$) on average correlation. Across
274 all size thresholds the SDS ($\bar{r}_S = 0.965 \pm 0.035$), COMB ($\bar{r}_S = 0.954 \pm 0.037$), and RCS
275 ($\bar{r}_S = 0.949 \pm 0.049$) models produced the highest correlations respectively. Among these, none
276 were significantly different from each other. Again, chronologies produced by CD produced the
277 lowest correlations of all models ($\bar{r}_S = 0.785 \pm 0.074$), ($p < 0.001$, all cases). BAI produced
278 chronologies ($\bar{r}_S = 0.922 \pm 0.177$) performed significantly worse than SDS, COMB and RCS
279 chronologies and significantly better than CD ($p < 0.001$, all cases). Tukey HSD contrasts
280 suggested that the significant effect of minimum size threshold was again driven by significant
281 differences in correlations between BAI produced chronologies among samples. As evident in
282 Figure 2b, BAI chronologies performed significantly better when sampling size thresholds

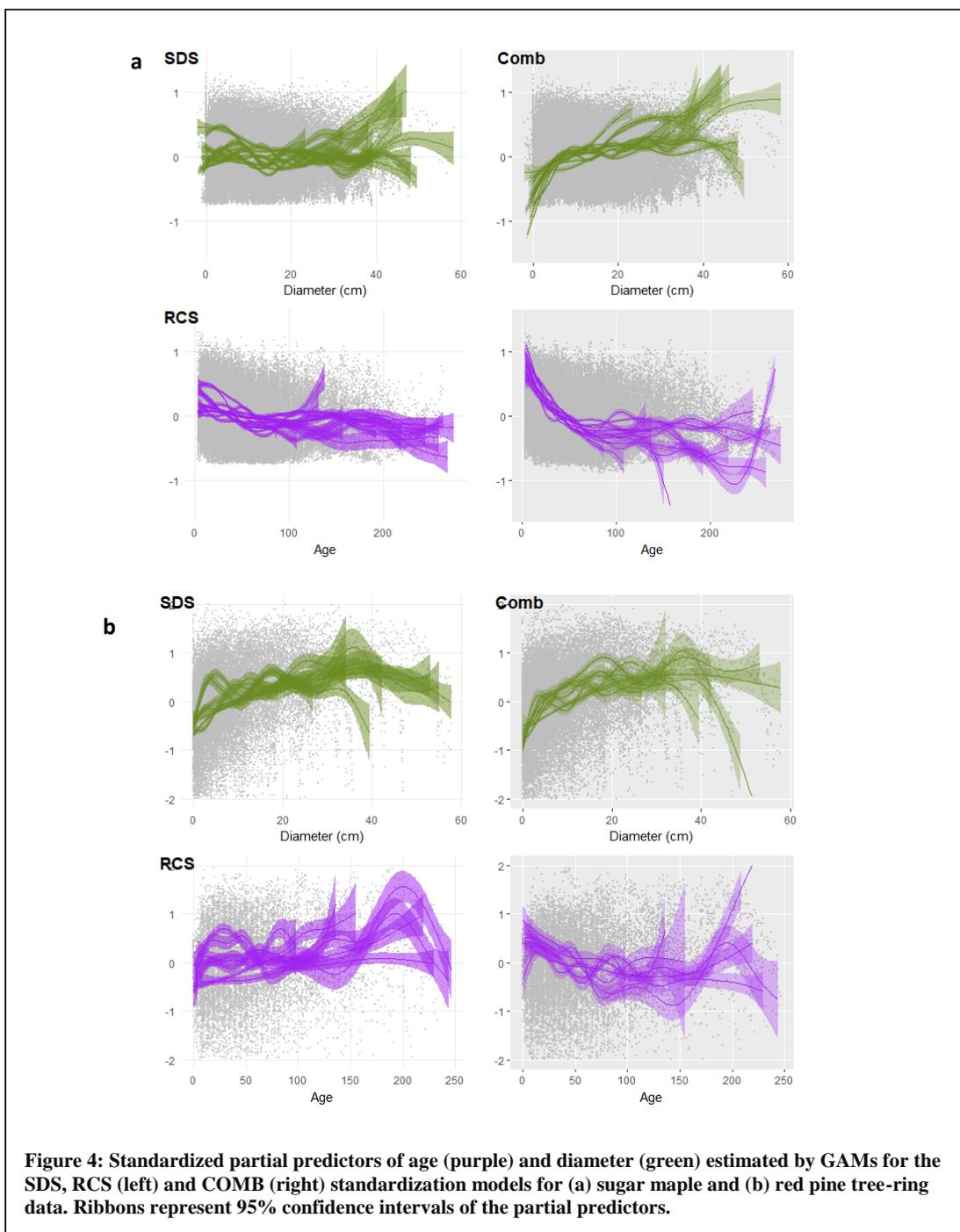


283 exceed 30 cm DBH ($p < 0.001$, all cases). However, for BAI chronologies increased size
284 thresholds of 50 cm DBH did not produce significantly higher correlations relative to the 30 cm
285 DBH threshold ($p = 1.000$). Bootstrapped white pine chronologies produced by each of the
286 standardization methods are provided in Figure 3b.

287 When comparing mean correlations produced by each method between sugar maple and white
288 pine, two-way ANOVA suggested a significant interaction between species and method
289 ($p < 0.001$). Tukey HSD contrasts suggested this effect is driven by significant differences in
290 correlations produced by RCS, BAI and CD between species. More specifically, across all size
291 thresholds RCS and CD produced significantly higher correlations in white pine relative to sugar
292 maple ($p = 0.011$, $p < 0.001$, respectively). Whereas, BAI produced significantly higher
293 correlations in sugar maple ($p < 0.001$).

294 **3.2 Comparisons of methods in real tree-ring data**

295 The standardized partial predictors estimated for each of the SDS, RCS and COMB models fit to
296 the sugar maple and red spruce data are provided in Figure 4. In general, SDS and RCS models
297 suggested rather flat relationships between tree age and size with in average growth (log-
298 transformed) in both species. However, when the effects of age and tree size were considered
299 together in COMB models both showed more distinct relationships with average growth. In the
300 COMB models average tree growth appeared to increase rapidly with tree size and eventually
301 decline as trees exceed 50 cm DBH in both species. Average growth appeared to decline with
302 increasing age before leveling off around 100 years. In both cases the COMB models showed
303 better agreement among sites in small/young trees than the simpler models.



304

305 In sugar maple, Tukey HSD contrasts suggested no significant differences in the meaningful AIC
306 comparisons after controlling for site differences (Fig. 5a). However, R^2 produced by the COMB



307 models were significantly higher than those produced by both the SDS ($p=0.039$) and RCS
308 ($p<0.001$) models, but SDS and COMB were not significantly different from each other
309 ($p=0.177$), (Fig. 5a). LMEs did not suggest a significant effect of model choice on any of the
310 chronology quality statistics (mean interseries-correlation, SNR, EPS).

311 In red spruce, the COMB model fits exhibited
312 significantly lower AIC values than the SDS model
313 ($p<0.001$) after controlling for site differences (Fig.
314 5b). Similarly, the COMB_{red} model fits exhibited
315 significantly lower AIC values than the SDS_{red}
316 ($p<0.001$) and RCS ($p<0.001$) models, while the
317 SDS_{red} and RCS were not significantly different
318 from each other ($p=0.706$), (Fig. 5a). Similarly, R^2
319 produced by the COMB models were significantly
320 higher than those produced by both SDS ($p<0.001$)
321 and RCS ($p<0.001$), which were not different from
322 each other ($p=0.114$), (Fig. 5a). As with sugar
323 maple LME did not suggest a significant effect of
324 model choice on any of the chronology quality
325 statistics.

326 4 Discussion

327 4.1 Size-vs age-deterministic models for long-term trend reconstruction

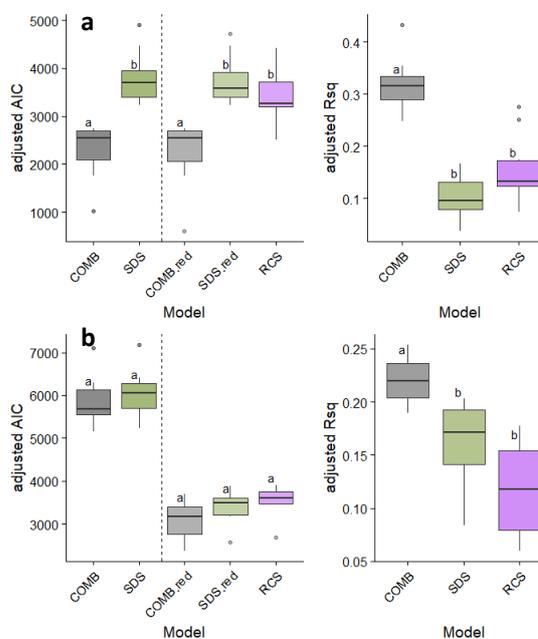


Figure 5: Adjusted AIC and R^2 values for fits of standardization models applied to (a) 7 sugar maple and (b) 11 red spruce tree-ring chronologies. Site-specific error was removed via a mixed modelling approach. Significant differences ($\alpha=0.05$) between models are indicated with small letters (a, b). Dashed vertical lines signify meaningful pairwise AIC comparisons (i.e. COMB vs. SDS).



328 Using simulated tree-ring data, from the shade-tolerant species sugar maple, we have shown that
329 standardization models which include tree size in the year of ring formation (SDS, COMB)
330 produced chronologies that retain long-term/low-frequency variation better than those produced
331 by models that only include age as a predictor (RCS). Alternatively, in the shade-intolerant
332 species white pine, chronologies produced by the SDS, RCS and COMB models showed no
333 significant difference in their estimation of long-term trends. Further, our analysis suggests that
334 the traditional RCS method performed significantly worse in the shade-tolerant species, sugar
335 maple, than in shade-intolerant white pine.

336 The finding that size-based standardization models performed well in simulated tree-ring data is
337 not surprising given that the SORTIE model calculates annual tree growth as function of tree
338 size. Thus, the underlying growth-trend would be well-approximated by a flexible curve
339 estimated on the basis of tree size. As such, we use these results solely to elucidate the
340 problematic nature of age-based standardization methods for shade-tolerant species. SORTIE's
341 use of diameter, rather than age, as a determinant of tree growth is not arbitrary; it is well
342 established that tree metabolic processes are directly related to size (West et al. 2001).
343 Additionally, there is little evidence for a unique effect of age on tree growth that is independent
344 of size (Munné-Bosch 2007 (and within)). With the exception of dendrochronological models,
345 the vast majority of individual tree growth and process models are indeed size-based. It follows
346 that the ubiquitous use of age or calendar year in tree-ring standardization methods (RCS, signal-
347 free standardization, C-method, CD, Hugeshoff curves) is a practice born out of convenience
348 rather than physiological consideration. As such, we agree with previous accounts that this
349 assumption may be especially problematic in shade-tolerant trees where age and size may not be
350 perfectly correlated (Peters et al. 2015, Bontemps and Esper 2011).



351 Unfortunately, all systematic comparisons of tree-ring standardization methods in real tree-ring
352 data (e.g. Sullivan et al. 2016) are limited by their inability to validate long-term trends estimated
353 by chronologies. Instead, we evaluate standardization models on the basis of model parsimony.
354 We have shown that in the shade-tolerant species red spruce, COMB models are significantly
355 more parsimonious (estimated by AIC) than simpler models (RCS, SDS). Further, the COMB
356 models explain more variance (estimated by R^2) in tree-ring data regardless of differences in
357 underlying sample sizes. Overall, our results are conservative relative to similar comparisons
358 performed by Nock et al. (2011) in tropical tree species of varying shade-tolerance. Nock et al.
359 (2011) note that LMEs of BAI that included tree diameter had more support than those that
360 included age. In line with discussion above, Nock et al. (2011) attribute this finding to size being
361 a more important determinant of light capture as it relates to tree height and crown size (King et
362 al. 2005). Further, in both red spruce and sugar maple we have shown that tree size and age
363 exhibit stronger relationships with average growth when their unique effects are estimated
364 simultaneously in COMB models rather than alone in SDS and RCS models, respectively. This
365 result is interesting given the high correlation expected between these variables and it may
366 explain why COMB models explained significantly more variance than each of the simpler
367 models. Given the relatively weak trends shown in predictors from both the SDS and RCS,
368 models we suggest that low-frequency variance related to the underlying biological growth-trend
369 may be retained in these chronologies.

370 Regardless of differences in model fits, the implications for the resultant chronologies remain
371 conservative (Fig. S.2). Similarly, in comparison of RCS and SDS chronologies in common
372 beech (*Fagus sylvatica* L.) Bontemps and Esper (2011) note both chronologies exhibit similar
373 annual variations. The resultant chronology is more likely to be influenced by sample size of the



374 underlying tree population than by choice of standardization model. Tree age can be difficult or
375 impossible to accurately estimate for some trees. In contrast, annual tree size can be reliability
376 estimated from DBH and tree-ring measurements more ubiquitously. We note that in this study
377 only 66% of sugar maple trees could be accurately aged. Since unaged trees are likely to be the
378 oldest trees in the chronology, it follows that RCS chronologies may exhibit poor sample
379 replication (especially in early years) and may be significantly shorter than those produced by
380 SDS or COMB models. This has obvious implications for data quality and suitability.
381 Considerably problematic is the “segment length curse” whereby, almost all standardization
382 methods are ill-equipped to estimate long-term trends on time scales greater than or equal to the
383 length of the chronology itself (Cook et al. 2005). Excessively short RCS chronologies are
384 therefore limited in their application. A large advantage of SDS and COMB models is that they
385 can incorporate otherwise inadmissible tree-ring data.

386 **4.2 BAI and CD methods for long-term trend reconstruction**

387 The finding that CD did not produce accurate long-term trends in simulated tree-ring data is
388 consistent with our expectations (Peters et al. 2015, Briffa et al. 1992). We maintain CD should
389 be avoided if the goal is long-term reconstruction from tree-ring data.

390 BAI chronologies accurately reproduced long-term trends in simulated tree-ring data. However,
391 our analysis suggests BAI is less reliable when small/young trees are sampled. This was in line
392 with Peters et al. (2015) who note high accuracy and sensitivity of BAI chronologies to imposed
393 long-term trends, but that BAI is likely to produce erroneous trends when the underlying trend is
394 of low signal, as would be the case for young/small trees that have low BAI rates and low
395 climate sensitivity. As presented here, the BAI method imparts a strict relationship between tree
396 size and growth. It has been suggested that this relationship may not account for the entire



397 biological growth-trend (Peters et al. 2015). Accordingly, we caution future studies in their
398 interpretation of BAI trends in low-signal tree-ring series. Alternatively, other studies have
399 explicitly modelled size and/or age effects on BAI using a mixed-effect modelling approach (e.g.
400 Marqués et al. 2016, Camarero et al. 2015, Nock et al. 2011, Martínez-Vilalta et al. 2008). We
401 suggest this approach may better account for species- and site-specific factors that influence
402 expected growth rates, leading to more accurate estimates of long-term trends in the resultant
403 chronology. While our findings regarding the importance of inclusion of size in tree-ring
404 standardization models are presented in the context of raw tree-ring width models, they are also
405 directly relevant to explicit models of BAI.

406 **4.3 Other considerations and future research**

407 It is important to note that the goal of this study was not to explicitly test the effect of sample
408 biases (i.e. modern sample bias, selection bias, etc.) on trend reconstruction, but instead to assess
409 reliability across different underlying sampling distributions. There is now considerable evidence
410 to suggest that the long-standing practice of sampling only dominant trees or trees exceeding a
411 minimum size threshold within a stand leads to considerable bias in the resultant chronology
412 (Nehrbass-Ahles et al. 2014, Brienen et al. 2012, Briffa and Melvin 2011). This bias is consistent
413 across standardization methods (Nehrbass-Ahles et al. 2014). We maintain that in cases of long-
414 term trend reconstruction, stands should be sampled according to the underlying stand age/size
415 distribution, either through use of fixed-plots or random tree selection, regardless of the
416 standardization procedure used.

417 Our study has suggested that the choice of standardization model (SDS, RCS, COMB) has no
418 discernable effect on indices of chronology quality (EPS, SNR, interseries-correlation). We
419 suggest this finding is a result of the chosen species exhibiting low climate sensitivity (Phipps



420 1982) and thus, low common signal in the chronology. As such we do not regard this finding as
421 failure of any of the standardization models. We suspect more conclusive results would be found
422 in climate sensitive species. Given the underlying physiological justification of the models
423 presented here, we have no reason to suggest they are not broadly applicable to species of all
424 shade-tolerance levels. We recommend future studies investigate the applicability of SDS and
425 COMB models to both raw tree-ring width and BAI data in wider range of species. That said,
426 shade-tolerant and broadleaf species, and their applicable standardization procedures, are
427 underrepresented in dendrochronological studies (Zhao et al. 2019). We advocate for continued
428 refinement of tree-ring standardization procedures that are relevant to the ecological questions
429 they aim to address.

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