

Blue Intensity based experiments for reconstructing North Pacific temperatures along the Gulf of Alaska

Rob Wilson^{1,2}; Rosanne D'Arrigo,²; Laia Andreu-Hayles²; R. Oelkers,²; Greg Wiles^{2,3};
Kevin Anchukaitis^{4,2} and Nicole Davi^{2,5}

1. University of Saint Andrews, Saint Andrews, UK; 2. Tree-Ring Laboratory, Lamont-Doherty Earth Observatory, Palisades, NY, USA; 3. The College of Wooster, Wooster, Ohio; 4. School of Geography and Development & Laboratory of Tree Ring Research, University of Arizona, Tucson, AZ USA 5. William Paterson University, New Jersey, USA.

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Abstract: Ring-width (RW) records from the GOA have yielded a valuable long-term perspective for North Pacific changes on decadal to longer time scales in prior studies, but contain a broad winter to late summer seasonal climate response. Similar to the highly climate-sensitive maximum latewood density (MXD) proxy, the Blue Intensity (BI) parameter has recently been shown to correlate well with year-to-year warm-season temperatures for a number of sites at northern latitudes. Since BI records are much less labor intensive and expensive to generate than MXD, such data hold great potential value for future tree-ring studies in the GOA and other regions in mid-to-high latitudes. Here we explore the potential for improving tree-ring based reconstructions using combinations of RW and BI-related parameters (latewood BI and delta BI) from an experimental sub-set of samples at eight mountain hemlock (*Tsuga mertensiana*) sites along the GOA. This is the first study for the hemlock genus using BI data. We find that using either inverted latewood BI (LWB_{inv}) or delta BI (DB) can improve the amount of explained temperature variance by > 10% compared to RW alone, although the optimal target season shrinks to June-September, which may have implications for studying ocean-atmosphere variability in the region. One challenge in building these BI records is that resin extraction did not remove colour differences between the heartwood and sapwood, so long term trend biases, expressed as relatively warm temperatures in the 18th century, were noted when using the LWB_{inv} data. Using DB appeared to overcome these trend biases resulting in a reconstruction expressing 18th-19th century temperatures ca. 0.5°C cooler than the 20th/21st centuries. This cool period agrees well with previous dendroclimatic studies and the glacial advance record in the region. Continuing BI measurement in the GOA region must focus on sampling and measuring more trees per site (> 20) and compiling more sites to overcome site-specific factors affecting climate response and using sub-fossil material to extend the record. Although LWB_{inv} captures the inter-annual climate signal more strongly than DB, DB appears to better capture long term secular trends that agree with other proxy archives in the region. Great care is needed, however, when implementing different detrending options and more experimentation is necessary to assess the utility of DB for different conifer species around the Northern Hemisphere.

38

39 **Keywords:** Blue Intensity, Gulf of Alaska, Tree Rings, Reconstruction, North Pacific; **Short**
40 **Title:** Gulf of Alaska Blue Intensity Tree-Ring Temperature Reconstruction

41

42 **1. Introduction**

43 The climate of the Gulf of Alaska (GOA) is strongly influenced by the atmosphere-ocean
44 variability of the North Pacific sector (e.g. the Pacific Decadal Oscillation, Mantua et al. 1997),
45 with profound socioeconomic implications for the region (Ebbesmeyer et al. 1991). The variability
46 of such synoptic climate phenomena is more strongly expressed in winter. Ring-width (RW) data
47 measured from montane treeline conifer trees in the GOA region often express a broad seasonal
48 response window (e.g. January-September, Wilson et al. 2007; February-August, Wiles et al.
49 2014), which has allowed such data to provide information on cold season synoptic dynamics
50 covering almost two thousand years (Barclay et al. 1999, D'Arrigo et al. 2001, Wiles et al. 2004
51 and 2014, Wilson et al. 2007).

52

53 Maximum-latewood density (MXD) measurements have yielded long records of past summer
54 temperatures for many regions in the northern mid-to-high latitudes (e.g. Schweingruber 1988,
55 Briffa et al. 2002, Anchukaitis et al. 2013, Schneider et al. 2015), but such records do not yet exist
56 for the GOA. MXD series are particularly desirable as such records often have stronger
57 correlations with temperatures than RW and result in climate reconstructions with better skill and
58 spectral fidelity (Anchukaitis et al. 2013, Esper et al. 2015, Wilson et al. 2016, Anchukaitis et al.
59 2017). This is partly because RW chronologies typically exhibit higher autocorrelation and lagged
60 memory effects than MXD (Briffa et al. 2002; Anchukaitis et al. 2012), but also because RW may
61 potentially integrate other ecological signals (e.g. disturbance and stand dynamics) which can

62 obscure the climate signal (Rydval et al. 2015). Yet, only two millennial-length MXD records are
63 currently published for all of north-western North America (Icefields, British Columbia (BC),
64 Canada - Luckman and Wilson 2005; Firth River, Alaska - Andreu-Hayles et al. 2011, Anchukaitis
65 et al. 2013) and no MXD data have been generated to date for the entire GOA. This situation
66 partly relates to the expensive and labor intensive nature of MXD measurement, but also because
67 the wood of mountain hemlock (*Tsuga mertensiana*), a dominant conifer species in the GOA, is
68 rather brittle and does not lend itself well to standard sample preparation for MXD measurement.
69

70 To help meet the need for additional climatically-sensitive density records from north-western
71 North America, we present herein an exploration of novel Blue Intensity (BI) parameters measured
72 from scanned images of tree core samples from the GOA. Minimum latewood blue intensity
73 (LWB) has recently been shown to have strong similarities to MXD, and is much cheaper and
74 simpler to generate (McCarroll et al. 2002; Björklund et al. 2014, 2015; Rydval et al. 2014; Wilson
75 et al. 2014, 2017). LWB is closely related to MXD as they both measure similar wood properties
76 (combined hemicellulose, cellulose and lignin content related to cell wall thickness), and both are
77 well correlated with warm-season temperatures (Campbell et al. 2007; Björklund et al. 2014,
78 Rydval et al. 2014, Wilson et al. 2014). This correspondence between BI and temperature has
79 recently been shown to hold true for several locations and tree species, including Scots pine (*Pinus*
80 *sylvestris*) in Scotland, UK (Rydval et al. 2014) and Sweden (Björklund et al. 2014, 2015),
81 Caucasian fir (*Abies nordmanniana*) in the Northern Caucasus' (Dolgova 2016), Stone pine (*Pinus*
82 *cembra*) in Austria (Wilson et al. 2017), Engelmann spruce (*Picea engelmannii*) from the Canadian
83 Rockies, British Columbia, Canada (Wilson et al. 2014) and our own analyses of white spruce
84 (*Picea glauca*) in north-western North America (Andreu-Hayles et al., ms. in prep.). Although BI

85 often requires larger sample sizes than MXD to improve signal strength (Wilson et al. 2014), this
86 is not a concern due to the low cost of the method.

87
88 The greatest limitation of LWB, however, is that any colour variation that does not represent year-
89 to-year climate-driven cell wall thickness changes will bias the resultant raw reflectance
90 measurements. For example, some conifer species (including Scots pine and mountain hemlock)
91 show a clear sharp or transitional colour change from the heartwood to sapwood, which, even after
92 resin extraction using ethanol or acetone, can still impose a systematic change in reflectance
93 around the heartwood/sapwood transition (Rydval et al. 2014; Björklund et al. 2014, 2015). Further
94 colour variations, often seen in dead but preserved snag or sub-fossil wood, can also result in
95 systematic biases when combined with data measured from living samples (Björklund et al. 2014,
96 2015; Rydval et al. 2014). Björklund et al. (2014) proposed a potential solution to the
97 heartwood/sapwood colour bias issue by effectively detrending the LWB measurements by
98 removing the inherent common colour changes of the earlywood and latewood (i.e. those related
99 to heartwood/sapwood colour change). This is accomplished by subtracting the raw LWB value
100 from the maximum blue reflectance value of the earlywood (EWB) for each year. The resulting
101 new parameter, delta blue intensity (hereafter referred to as DB), should theoretically be less biased
102 by such non-climatic related colour changes. Although Björklund et al. (2014, 2015) presented
103 compelling results using Scots pine in Sweden, DB has not yet been tested elsewhere or on any
104 other species.

105
106 Finally, although BI based variables hold great promise as an alternative proxy to MXD, another
107 potential concern is the possibility that reflectance based measurements may not capture low

108 frequency information related to long term-climate changes. Wilson et al. (2014), working with
109 Engelmann spruce from British Columbia, which does not have a visual colour difference between
110 the heartwood and sapwood, urged caution as both the MXD and LWB parameters were sensitive
111 to different detrending options and there was some indication that LWB could not capture as much
112 low frequency information as MXD. However, this observation could not be fully addressed due
113 to the relatively short instrumental record in British Columbia.

114
115 In this paper, building upon previous RW based research (Wilson et al. 2007, Wiles et al. 2014),
116 we measure BI variables (EWB, LWB and DB) from multiple sites in the GOA to evaluate: (a)
117 whether BI can improve on previous RW-only based reconstructions, and (b) whether meaningful
118 low frequency information can be gleaned from these data by exploiting the long monthly
119 instrumental record from Sitka, Alaska back into the mid-19th century to validate secular trends in
120 the TR data.

121

122

123 **2. Methods and Analysis**

124

125 For this exploratory study, BI measurements were made on a subset (ca. 15 single tree cores per
126 site) of crossdated core samples collected over the past few decades from living mountain hemlock
127 (*Tsuga mertensiana* Bong. Carrière) trees located at eight sites near altitudinal treeline
128 (approximately ~300-400 meters above sea level) along the GOA (Table 1, Figure 1). Data from
129 these and additional sites were used previously to create coastal GOA RW based temperature-
130 related reconstructions (D'Arrigo et al. 2001, Wilson et al. 2007, Wiles et al. 2014).

131

132 The tree core samples were immersed in acetone for 72 hours to remove excess resins in the wood
133 (Rydval et al. 2014) and then finely sanded to 1200 grit to remove marks and abrasions prior to
134 scanning. An Epson V850 pro scanner, using an IT8.7/2 calibration card in conjunction with
135 Silverfast scanning software, was used to scan the samples at 2400 dpi resolution. Raw EWB and
136 LWB variables were measured using Coorecorder 8.1 software (Cybis 2016 -
137 <http://www.cybis.se/forfun/dendro/index.htm>), which has capabilities to acquire accurate
138 reflectance intensity RGB colour measurements from scanned wood samples (see Rydval et al.
139 2014). DB values were calculated within Coorecorder by subtracting the raw LWB values from
140 the raw EWB values for each year. Since raw LWB is negatively correlated to MXD (high density
141 'dark' latewood = low reflectance), values were inverted following the method detailed in Rydval
142 et al. (2014) to allow for LWB (hereafter denoted as LWB_{inv}) to be detrended in a similar way to
143 MXD (see also Wilson et al. 2014). The nature of the DB calculation results in this parameter
144 being positively correlated with LWB_{inv} , so these data could also be theoretically detrended in a
145 similar way. It should be noted that Björklund et al. (2014) proposed that LWB_{inv} should be
146 referred to as maximum latewood blue absorption intensity.

147
148 As the mean sample length (Table 1) for all sites was > 200 years, for initial experiments
149 comparing the different tree-ring (TR) variables, the RW, LWB_{inv} , EWB and DB data were
150 detrended using fixed 200-year cubic smoothing splines (Cook and Peter 1981) to retain the
151 interannual to multi-decadal signal and minimize any potential lower frequency biases due to
152 heartwood/sapwood colour changes. The variance of the site and regional composite chronologies
153 were temporally stabilized using techniques detailed in Frank et al. (2007a). These chronology
154 versions were assessed by (1) signal strength statistics: both common signal (via mean inter-series

155 correlation – RBAR) and expressed population signal (EPS - Wigley et al. 1984) statistics, (2)
156 between variable correlation, (3) between site coherence using a rotated principal component
157 analysis (PCA, varimax rotation using correlation matrices with eigenvectors retained with an
158 eigenvalue > 1.0) and (4) climate response derived by correlations between regional composite TR
159 variable mean series and the dominant PC scores against monthly and season variables of
160 temperature (CRU TS 3.24 (Harris et al. 2012): 57-61°N / 153-134°W).

161
162 The 200-year spline chronology versions were also used to explore calibration (1901-1960) and
163 validation (1961-1989) based principal component regression reconstruction experiments using
164 the CRU TS data. The 1961-1989 period was specifically used for validation as many tree-ring
165 width based temperature sensitive chronologies in Alaska do not track recent temperature trends
166 well – a phenomenon often referred to as the “Divergence Problem” (D’Arrigo et al. 2008). For
167 the PCA, a reasonably replicated common period (1792-1989) was used where tree series
168 replication was > 5 trees. All site chronologies are replicated with > 10 trees from 1792 except for
169 JM and SR (see Table 1) where replication is 6 and 5, respectively. Reconstruction validation was
170 performed using the Pearson’s correlation coefficient (r), the Reduction of Error (RE) and the
171 Coefficient of Efficiency (CE - Cook et al., 1994). Further validation was performed over the 1850-
172 1900 period using the gridded BEST instrumental data (Rohde et al., 2012), extracted for the same
173 region as the CRU TS (57-61°N / 153-134°W), after these data were scaled to the CRU TS data
174 over the 1901-2015 period. CRU TS and BEST are compared (Supplementary Figure S1) to the
175 original GOA 5-station mean records used in Wilson et al. (2007) to confirm that the gridded
176 products are good representations of the regional temperature signal. The higher variance of the
177 pre-1950 period in the 5-station mean is related to the fact that variance stabilization (Frank et al.

178 2007a) was not performed when this mean series was originally developed (Wilson et al. 2007)
179 and is therefore likely a less robust measure of GOA temperatures than the gridded products.

180

181 Finally, to improve overall expressed signal strength and explore the potential of reconstructing
182 robust low frequency temperature changes in the region, the data from each of the eight sites were
183 pooled to derive GOA regional composite records for each of the TR variables. These pooled
184 composite variable datasets, with their greater overall replication, allowed detrending experiments
185 to be performed to ascertain the sensitivity of the final parameter chronologies to different
186 detrending choices. Specifically, RW detrending experiments were performed using (1) STD:
187 negative exponential function or negative or zero slope linear function detrending via division; (2)
188 NEPT: negative exponential function or negative or zero slope linear function detrending via
189 subtraction after power transformation of the raw RW data (Cook and Peters 1997); and (3) RCS:
190 single group regional curve standardization (RCS - Briffa et al., 1996; Esper et al., 2003; Briffa
191 and Melvin 2008) detrending via division. The regional age-aligned curve was smoothed using a
192 cubic smoothing spline (Cook and Peters 1981) of 10% the series length. For each of these three
193 approaches, the 'Signal-Free' (SF - Melvin and Briffa 2008) approach to detrending was also used.
194 Finally, the composite chronologies, also using the SF approach, were also derived using the age
195 dependent spline (ADS) approach introduced by Melvin et al. (2007) to track more complex
196 growth trends that may not be captured well with the STD, NEPT and RCS approaches. These
197 different detrending options resulted in an ensemble of 7 different RW composite chronologies.
198 For LWB_{inv} and DB, as they theoretically should behave more like MXD, which often has a
199 decreasing linear trend, detrending was performed using (1) LINres: negative or zero slope linear
200 function detrending via subtraction - with and without the SF approach; (2) RCSres: single group

201 RCS detrending via subtraction - with and without the SF approach; and (3) ADSsf: the signal free
202 age dependent spline approach. Overall, for LWB_{inv} and DB, five chronology variants were
203 developed for analysis.

204

205 **3. Results and Discussion**

206 **Common signal within the network**

207 RW has the strongest common signal with a median overall RBAR of 0.44 (8 site range: 0.33 –
208 0.49 - Table 1), whereas LWB_{inv} and DB both have weaker RBAR values of 0.24. EWB shows the
209 weakest common signal with a median RBAR from the 8 sites of only 0.12. In order of decreasing
210 between-series common signal, the number of trees needed to attain an EPS of 0.85 are 7 (RW),
211 18 (LWB_{inv} and DB), and 41 (EWB) for each variable respectively. On average, therefore, except
212 for RW, actual replication for the reflectance based parameter chronologies are often lower than
213 would be ideally needed to attain a robust expressed population signal. This is important to keep
214 in mind as it is likely that the experimental calibration results presented herein will improve as
215 replication is increased.

216

217 The weak signal strength in EWB compared to RW, LWB_{inv} and DB is also reflected in the PCA.
218 The leading PC for RW, LWB_{inv} and DB explains 59%, 53% and 57% of the overall variance,
219 respectively, while just 39% is explained by the EWB PC1. In general, the loadings (based on a
220 varimax rotation) of the chronologies on each PC for each variable are related to the geographical
221 locations across the GOA with PC1 representing the eastern sites and PC2 the western ones
222 (Figures 1 and 2). A similar spatial distribution of loadings was noted in Wilson et al. (2007) using
223 RW data from 31 living sites across the GOA.

224

225 **Seasonal temperature sensitivity**

226 EWB contains a weak response to summer temperature variability with almost no late summer
227 temperature signal (Figure 2) although some significant correlations ($r = \sim 0.3 - 0.4$) are found with
228 May and previous October/November temperatures (supplementary Figure S2). Correlations with
229 seasonal temperatures, after 1st differencing, identifies no significant response (supplementary
230 Figure S3). In agreement with previous work (Wilson et al. 2007; Wiles et al. 2014), RW correlates
231 well with a broad range of summer seasons (Figure 2), showing positive correlations for nearly all
232 months from January through to September (Supplementary Figure 2) with June returning the
233 strongest correlation. Correlations do weaken when the data are 1st differenced (supplementary
234 Figure S3), but the Wiles et al. (2014) RW composite still retains a strong response with February-
235 August temperatures although for the other RW based time-series, the summer season shows the
236 strongest coherence. LWB_{inv} and DB, show a weaker response with the late winter/spring months
237 compared to RW and strongest correlations with June, July and August (Figure 2). These
238 observations were expected as LWB_{inv} and DB should express similar growth/climate response
239 properties to MXD.

240

241 For the RW, LWB_{inv} and DB data, there appears to be a geographical difference in response with
242 PC1 (eastern sites) showing stronger seasonal (Figure 2) and monthly (supplementary Figure S2)
243 correlations with temperature than PC2 (western sites). However, correlations of the individual
244 site chronologies for each TR variable (Table 2) against June-September temperatures (optimal
245 season for reconstruction – see later) suggest that there is a degree of variability of the individual
246 sites' response to summer temperatures across the GOA. As PC2 is weighted more towards the

247 TBB site (see PCA loadings in Figure 2 for RW, LWB_{inv} and DB) which correlates weakly with
248 JJAS, it is therefore not surprising that this PC correlates weakly with summer temperatures. After
249 1st differencing, however, these regional differences disappear (supplementary Figure S3)
250 suggesting there are potential post-detrending trend biases in the chronologies weighted on PC2.

251
252 It is important to note that the correlation of the mean composite chronologies with summer
253 temperatures (Figure 2 and especially supplementary Figure S3 after a 1st differenced
254 transformation) are stronger than the PC1 results. This suggests that a regional mean composite
255 approach is potentially optimal in the context of deriving a GOA wide reconstruction which can
256 be extended in the future by data generated from sub-fossil samples.

257
258 The positive correlation of RW, LWB_{inv} and DB to summer temperatures (Figure 2 and Table 2)
259 is also reflected in the inter-correlation between these different variables (Table 3). RW agrees
260 most strongly with DB, followed by LWB_{inv}. EWB, unsurprisingly, has the weakest relationship
261 with the other 3 TR variables. Hereafter, due to the poor signal strength and weak climate signal,
262 the EWB data were not used for further analysis, except in the DB calculations.

263

264 **Calibration/validation experiments**

265 Calibration and validation statistics for various PC regression variable combinations for several
266 summer target seasons are detailed in Table 4 along with results using the GOA RW composite of
267 Wiles et al. (2014). Firstly, calibration of Wiles et al. (2014) to the CRU TS 3.24 data (February –
268 August) over the 1901-1989 period ($r^2 = 0.33$) is stronger than the new RW GOA composite ($r^2 =$
269 0.27) which also shows a significant trend in the model residuals. This residual trend possibly

270 reflects the fact that there could be a longer term trend missing in the RW data due to the use of
271 200-year spline detrended chronologies when compared to the RCS processed version of Wiles et
272 al. (2014). Also, the slightly weaker results for the new RW data likely reflect lower replication in
273 the current study compared to Wiles et al. (2014).

274
275 The strongest calibration a_r^2 values for each BI parameter over the 1901-1960 period are 0.49 and
276 0.47 for LWB_{inv} and DB respectively for the JJA season although DB fails validation with negative
277 RE and CE values over the 1961-1989 period. Minimal model improvement is gained by including
278 RW data. RW+ LWB_{inv} calibrates best ($a_r^2 = 0.49$) with JJA while RW+DB explains more
279 temperature variance for MJJAS ($a_r^2 = 0.51$). However, in both cases, validation RE and CE are
280 negative. Focussing on the full period (1901-1989) calibration, strongest results are found for the
281 JJAS season for all parameter options with a_r^2 values of 0.27 (RW), 0.43 (LWB_{inv}), 0.38 (DB),
282 0.38 (RW+ LWB_{inv}) and 0.39 (RW+DB) with no 1st order autocorrelation observed for any version.
283 Importantly, only the RW+DB version shows no significant linear trend in the model residuals.
284 The full period (1901-1989) calibrated reconstructions (Table 4) for each of the variable options
285 are presented in Figure 3 along with independent validation (1850-1900) with the BEST gridded
286 data. All parameter iterations fail validation (negative CE values) except for RW+DB which
287 returns positive RE (0.57) and CE (0.19) values. Overall, using this subset of samples from these
288 8 sites, the calibration results (Table 4 and Figure 3) indicate that BI based parameters explain
289 more temperature variance than using RW alone. However, the fidelity of the resultant
290 reconstructions appears sensitive to the periods of calibration and validation used and it is not clear
291 which of these parameters best represent longer term secular change as the chronologies were
292 limited in the frequency domain by using a fixed 200-year spline detrending option.

293
294 The large-scale climate signal expressed by these data is illustrated by comparing the RW+DB
295 JJAS reconstruction with gridded land/sea HadCRUT4 (Morice et al. 2012; Cowtan and Way 2014
296 – Figure 4a) and land only CRU TS 3.24 (Harris et al. 2012 – Figure 4b) temperatures for the GOA
297 and North Pacific sector. Although the spatial correlations are stronger towards Juneau and Sitka
298 (see Figure 1 for locations) in the east of the region it is clear that these new data represent the
299 temperature variability of the wider GOA region and North Pacific. Continued measurement of BI
300 based parameters from sub-fossil samples taken from across the GOA will allow long term summer
301 temperature variability to be derived for at least the last millennium which will complement the
302 long RW based temperature reconstructions expressing a broader seasonal window (Wilson et al.
303 2007; Wiles et al. 2014).

304

305 **Potential low frequency bias**

306 The main potential limitation to the use of BI based TR variables such as LWB is concerned with
307 low frequency trend biases related to wood colour change. Mountain hemlock, in general, shows
308 darker heartwood and lighter sapwood which resin extraction appears to only minimise but not
309 entirely remove. However, this colour change is not a sharp transition and is expressed in raw
310 EWB and LWB measurements as a steady increase in reflectance intensity. Non-detrended mean
311 composite chronologies of EWB and LWB for the whole GOA region (Figure 5) clearly show the
312 impact of the heartwood/sapwood colour change with increasing intensity values through time (see
313 also Supplementary Figure S4 for a single tree example), especially since the late 18th century. In
314 contrast, MXD generally shows a linear decreasing trend with increasing cambial age (Esper et al.
315 2012). If LWB is indeed a comparable (but inverted) TR variable to MXD as a measure of

316 latewood anatomical density properties, then we would expect, therefore, an increasing trend in
317 raw LWB values. Figure 5 therefore poses a potential “mixed-signal” conundrum as the observed
318 trend in the GOA raw mean LWB composite will incorporate the secular climate signal, the true
319 age-related trend of changing latewood density, and the heartwood/sapwood colour change bias.
320 Although using DB can theoretically overcome the colour bias issue, it has not been explored in
321 any detail beyond the original concept papers (Björklund et al. 2014, 2015). The mean DB non-
322 detrended GOA chronology (Figure 5) has minimal long term trends, which could suggest that the
323 colour change bias has been removed or at least minimised.

324
325 Mean cambial age-aligned curves of the EWB, LWB and DB data show very distinct trends
326 (Supplementary Figure S5). LWB appears to show a general linear increase in values – a trend that
327 would be expected if LWB indeed does reflect similar wood properties (inversely) to MXD. DB,
328 however, has a more complex mean growth curve, essentially reflecting trends in the EWB data,
329 and shows an initial increasing juvenile trend for ~50 years, a period of stabilisation and then a
330 decreasing trend from about ~200 to 300 years. These different age-aligned curves highlight that
331 different detrending options may well be needed for these different TR variables.

332
333 A range of credible options for detrending the RW, LWB_{inv} and DB GOA regional composite data
334 are presented in Figure 6. The outcome for the RW data appears extremely consistent even when
335 using STD vs RCS based methods. However, the LWB_{inv} and DB chronologies are much more
336 sensitive to the detrending method used. Compared to RW and DB, all LWB_{inv} chronology variants
337 show above zero index values in the 18th century, which likely reflects the low reflectance bias of
338 the darker heartwood compared to the sapwood because the LWB_{inv} data have been inverted. The

339 RCS versions appear particularly inflated and as LWB_{inv} is positively correlated with summer
340 temperatures (Figure 2), this would result in markedly warm temperature estimates during the LIA
341 compared to the 20th century which is at odds with previous GOA dendroclimatic analyses (Wiles
342 et al. 2014) and the geomorphological record, which indicate substantial cool conditions and
343 glacial advance from the 17th to 19th centuries (Wiles et al., 2004; Solomina et al. 2016). RCS can
344 impart significant low frequency bias when the assumptions and requirements of the method are
345 not met (Melvin and Briffa 2014; Anchukaitis et al. 2013) and as the GOA composite utilises only
346 living trees, this is a far from optimal sample design for this detrending method. For DB, the LINsf
347 version deviates markedly from LINres, RCSres, RCSsf and ADSsf variants with very low values
348 (< -6 standard deviation from 1901-1989 mean) before 1700 followed by a strong linear increase
349 until present. A similar observation was noted in Wilson et al. (2014) where signal free detrending
350 of LWB_{inv} and MXD resulted in much cooler LIA conditions than other detrending approaches.

351

352 **JJAS GOA summer temperatures back to 1600**

353 The long GOA instrumental record allows for additional assessment of how different reflectance
354 based chronology variants track temperatures back through time. Using the extended BI based
355 regional composite records, further reconstruction experiments against the JJAS season were
356 performed using LWB_{inv} and DB separately (Table 5) by calibrating against JJAS CRU TS3.24
357 (1901-2010) and separately validating using the BEST data (1850-1900). For the LWB_{inv} data, due
358 to their strong post 1970s decreasing trends (Figure 6), RCSres and RCSsf calibrated poorly (Table
359 5: $r^2 = 0.07$ and 0.05 respectively) and validated with negative CE values over the 1850-1900
360 period. LINres and LINsf explained 41% of the temperature variance while the ADSsf variant
361 explained 47%. All three versions validated reasonably well with positive RE and CE values.

362 Significant 1st-order autocorrelation (DW range 1.28 to 1.37) and linear trends (LINr range 0.36
363 to 0.48) were however noted for all model residuals except for ADSsf. For the DB data, calibration
364 was strongest for RCSsf, RCSres and ADSsf with positive RE and CE values for all versions
365 except ADSsf which failed the CE test. The residuals from the RCSsf, RCSres and ADSsf
366 calibrations show no 1st-order autocorrelation although a significant linear trend is observed.

367
368 Considering the calibration and validation experiments presented in Tables 4 and 5, our results do
369 not definitively identify whether LWB_{inv} or DB is the optimal BI based parameter for
370 reconstructing past summer temperatures for the GOA region. Part of this ambiguity potentially
371 stems from unknown uncertainties in the 19th century instrumental data, but the sensitivity of the
372 TR parameters to different detrending options (Figure 6) exacerbates the situation. Calibration
373 suggests that the inter-annual based signal of LWB_{inv} is marginally stronger than DB but validation
374 against the 19th century data cannot distinguish between the different parameters. The clear
375 differences between the chronology versions (Figure 6), especially before 1850, have huge
376 implications for understanding past temperatures in the region.

377
378 To try and derive a parameter specific view of long term temperature changes for the region, a
379 weighted mean using the five different variants were combined to create a regional average. The
380 r^2 values, derived from the 1901-2010 calibration (Table 5), was used as a weighting term to
381 calculate the parameter specific weighted averages which were then calibrated (1901-2010) and
382 validated (1850-1900) in the same way as detailed in Table 5. The resultant weighted LWB_{inv} and
383 DB regional reconstructions report quite different histories of past GOA temperatures (Figure 7).
384 Specifically, the LWB_{inv} reconstruction has temperature estimates from the late 17th to mid-19th

385 century warmer than the 1961-1990 mean, while the DB reconstructions exhibits generally cooler
386 conditions. Both reconstructions explain a similar amount of summer temperature variance
387 (LWB_{inv} : 43% vs. DB: 40%) and validate well with positive RE and CE values. The regression
388 residuals from both versions have a significant linear trend, but only for DB was no significant 1st
389 order autocorrelation identified in the residuals. From comparison to the instrumental data alone,
390 therefore, one cannot objectively identify which of the two parameter versions is most robust.
391 Wilson et al. (2014) highlighted the difficulties of relying solely on the instrumental data to
392 validate the long-term trend in any reconstruction. Moreover, there could be unknown
393 inhomogeneity issues in early instrumental data series which are difficult to identify which would
394 influence calibration and validation (see Frank et al. 2007b). Therefore, alternative sources of
395 relevant information are recommended for further validation. As the geomorphological record in
396 the region suggests a prolonged period of glacial advance occurred in the GOA up to the early 20th
397 century (Wiles et al., 2004; Solomina et al. 2016) when a substantial retreat started, we hypothesize
398 that the pre-1900 period must therefore have been cooler. This would suggest that the DB based
399 reconstruction is likely more representative of past GOA temperatures than the LWB_{inv} driven one.

400
401 Figure 8 presents the RW + DB principal component reconstruction (Figure 3), the weighted
402 LWB_{inv} and DB extended reconstructions (Figure 6), and the Wiles et al. (2014) RW based
403 reconstruction and compares them to the GOA regional glacial advance record (Wiles et al., 2004;
404 Solomina et al. 2016). The LWB_{inv} reconstruction is clearly at odds with the other records with
405 warmer than average temperatures for many periods over the last 400 years and no specific
406 prolonged cooler periods though the LIA. The other TR reconstructions demonstrate centennial
407 and multi-decadal agreement, although the extended DB reconstruction exhibits a smaller

408 amplitude of temperature change between the LIA period and the 20th century. Overall,
409 temperatures in the GOA region were below the 1961-90 norm throughout most of the LIA with
410 temperatures only rising to substantially higher values in the early 20th century. The coldest decadal
411 periods are centred around the 1700s, 1750s, and 1810s. The glacial advance record shows periods
412 of advance through the LIA, peaking at the end of the 19th century. Despite the use of 200-year
413 spline detrended chronologies, the RW+DB reconstruction has a similar amplitude change to the
414 Wiles et al. (2014) record, which was derived from RCS processed RW data. It should be noted
415 also that this RW based reconstruction was calibrated against Feb-August temperatures which has
416 a greater increasing temperature trend (0.81°C/century vs 0.62°C/century) and higher variance
417 (0.79 vs 0.41) than JJAS (calculated using BEST data from 1850-2015), which will influence the
418 amplitude of the reconstruction (Esper et al. 2005).

419

420 **4. Conclusions**

421 We have described a set of experimental temperature reconstructions based on RW, LWB_{inv} and
422 DB data measured from eight tree-ring sites along the Gulf of Alaska. Focusing on these data sets,
423 the results demonstrate that inclusion of BI based variables can significantly improve the calibrated
424 variance explained using RW alone by more than 10%.

425

426 RW, LWB_{inv} and DB are strongly correlated with each other (Table 3) but the inclusion of LWB_{inv}
427 or DB shifts the calibrated signal from a broad (February-August, Wiles et al. 2014) season using
428 RW alone to a late summer (JJAS) season. The influence of late winter and early spring
429 temperatures on RW suggest that this variable may, in fact, still be the more optimal variable for
430 studying important synoptic phenomena such as north Pacific variability, which dominates in the

431 winter months (Wilson et al. 2007).

432

433 The LWB_{inv} data, for mountain hemlock, despite calibrating and validating in a similar way to DB,
434 are clearly affected by heartwood/sapwood colour differences which impart a trend bias in the
435 resultant chronologies and reconstructions (Figures 6, 7 and 8). However, this bias may not
436 necessarily always occur for other species showing a heartwood/sapwood colour change which
437 could be removed through traditional resin extraction methods. For the first time since the original
438 concept papers by Björklund et al. (2014, 2015), we have experimented with the DB variable. The
439 resulting reconstruction agrees well with a previous RW based reconstruction (Wiles et al. 2014)
440 and the glacial advance record (Wiles et al., 2004; Solomina et al. 2016) for the region.

441

442 The analyses presented herein must be viewed as a series of experiments to inform
443 dendroclimatologists of possible methodological strategies that need to be considered for
444 improving TR based reconstructions using BI based variables. Specific to the GOA region, but
445 likely relevant to other regions and species, we therefore detail the following recommendations:

- 446
- 447 • Although MXD typically has a higher expressed population signal (EPS) strength and
448 climate responses than RW (Wilson and Luckman 2003), signal strength in LWB and DB
449 in GOA hemlock is weaker than RW, so replication needs to be substantially increased
450 (ideally > 20 trees – Table 1) to allow the development of robust chronologies. Rydval et
451 al. (2014) also showed that a substantial improvement in LWB signal strength could be
452 gained by measuring 2 or even 3 radii per tree. Additional assessments of signal strength
453 should be conducted as new species and sites are analysed using BI methods.
 - For conifer species with a clear colour difference between the heartwood and sapwood,

454 LWB_{inv} may likely always contain biased long-term trends. The DB variable could
455 potentially minimize this effect as shown here, but more experimentation with this
456 parameter is needed before it can be commonly used as a solution to the LWB_{inv} colour
457 bias problem. Rydval et al. (2017), using Scots pine, overcame the heartwood/sapwood
458 colour bias by utilising a band-pass approach to calibration, where LWB_{inv} drove the
459 decadal and high frequency fraction of the Scottish temperature reconstruction, while RW
460 drove the low frequency variability. This approach however assumes that (1) RW is
461 predominantly controlled by summer temperatures and (2) meaningful long-term
462 information can be gleaned from RW data, which may not always be the case (Esper et al.
463 2012).

464 • There is substantial sensitivity of the final chronologies to varying methodological
465 detrending approaches. Much more exploration of the impact of different detrending
466 choices is needed and it is likely that ensemble based approaches (Wilson et al. 2014) will
467 ultimately be the only way to derive realistic estimates and appropriate detrending based
468 uncertainties bounds. Locations with long instrumental records may help identify more
469 optimal detrending options but care is needed, as it cannot be assumed that the quality of
470 19th century data is comparable to late 20th/early 21st century data. Utilizing other proxy
471 observations of past climate (e.g. in this case the glacial record) may help further constrain
472 TR estimates of past climate especially when different chronology variants (that validate
473 well) portray quite different past temperature histories.

474

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482 **5. References**

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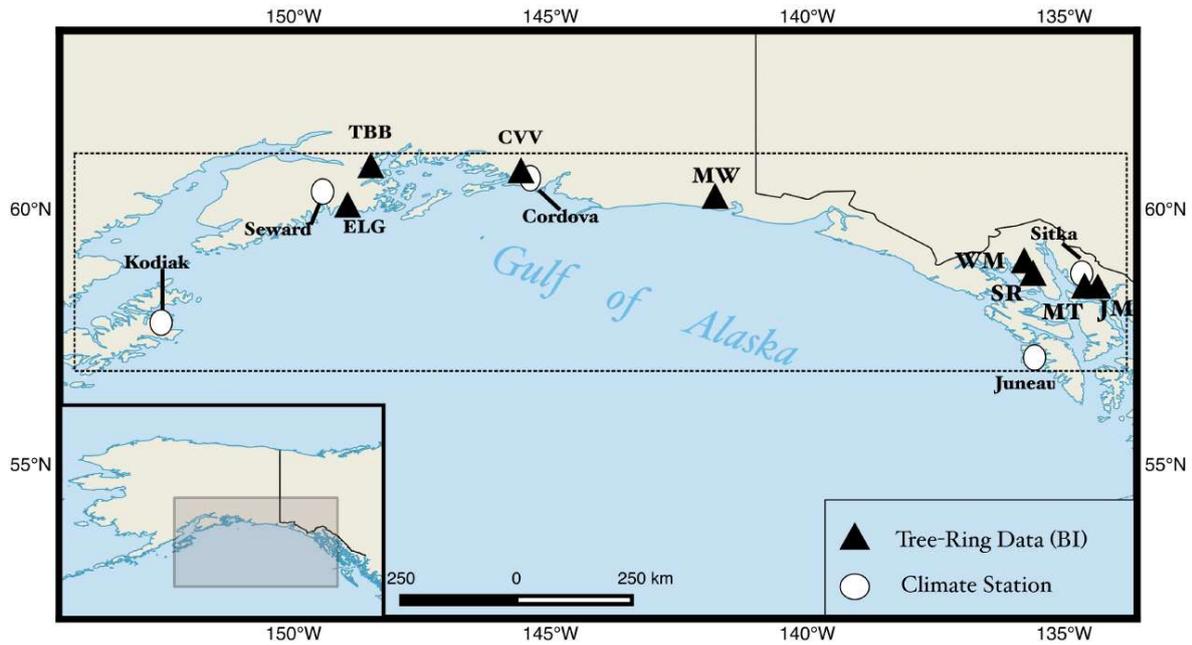
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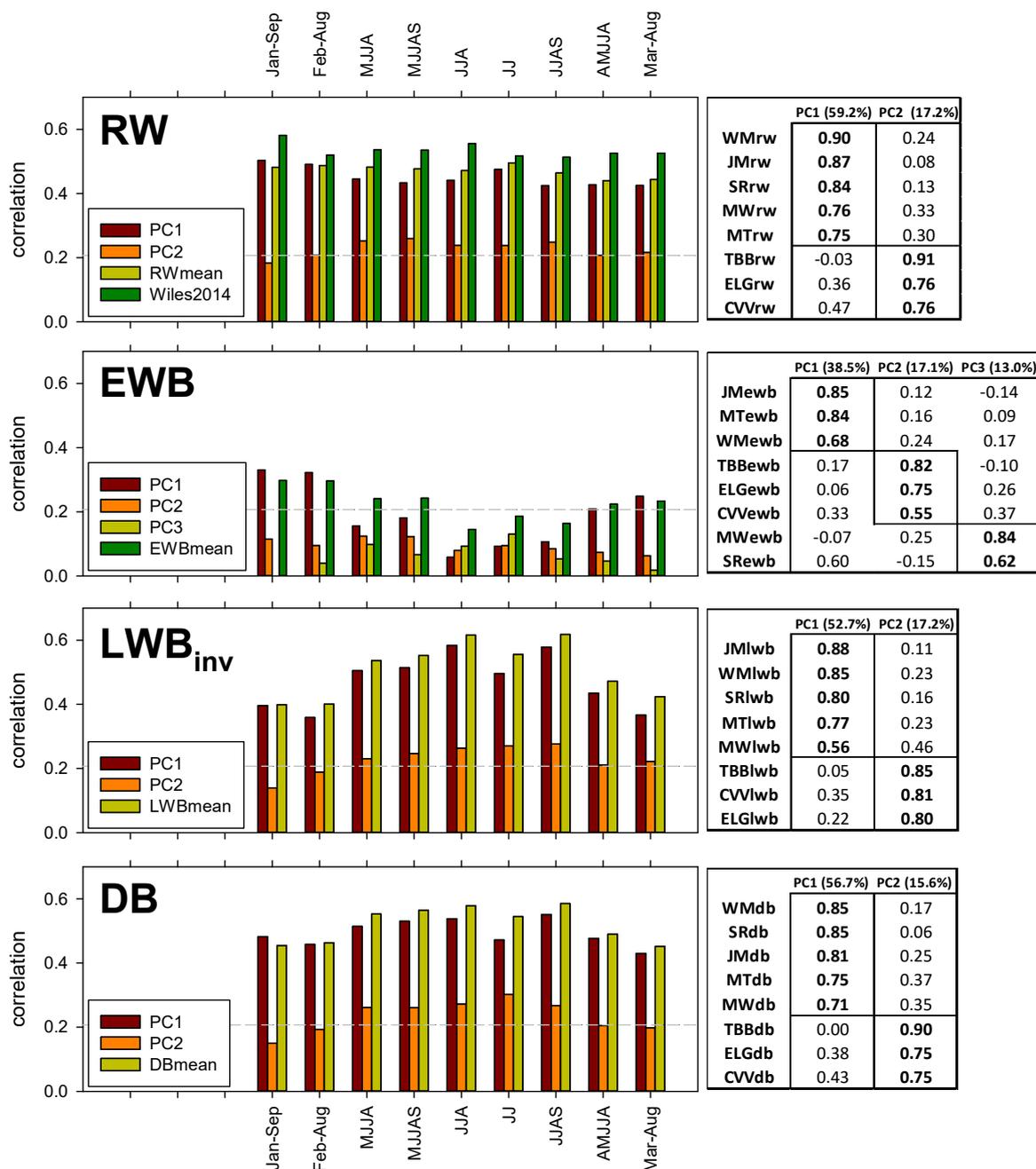
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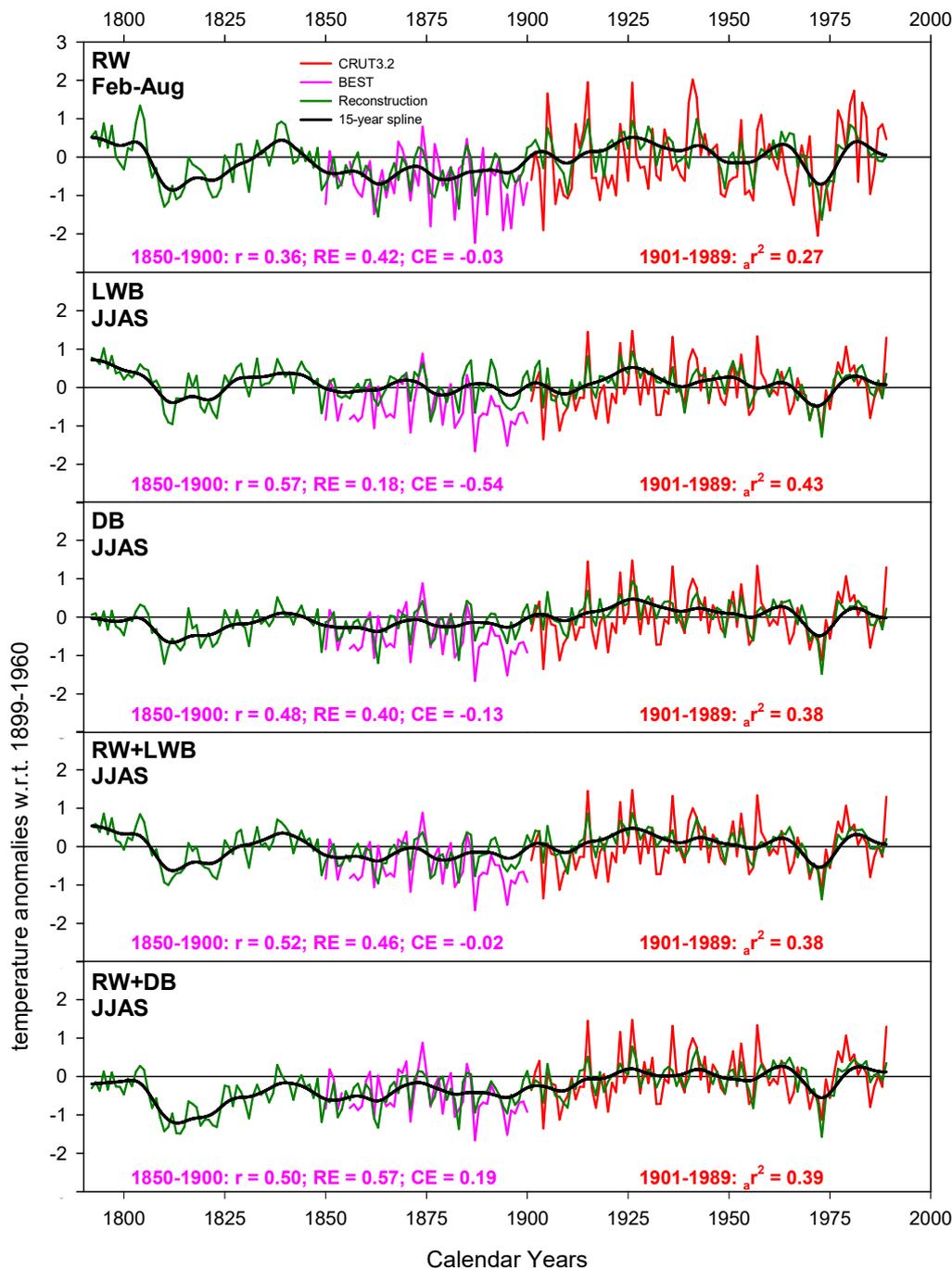
Figure 1: Location map of the eight GOA tree-ring sites used in this study (Table 1). Also indicated (dashed line box) is the domain (57-61°N / 153-134°W) of the gridded data (CRU TS 3.24, Harris et al. 2012; BEST, Rohde et al., 2012) used for calibration and the five coastal GOA temperature stations used in the original 5-station mean series (Wilson et al. 2007 – see supplementary Figure 1).



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Figure 2: Left: Correlation response function analysis (1901-1989) using CRU TS3.24 mean temperatures with each tree-ring variable (RW = ring-width; EWB = early wood maximum blue intensity; LWB_{inv} = inverted latewood minimum blue intensity; DB – Delta Blue). The bars represent correlations with seasonal temperature for each principal component (PC) score and the simple GOA mean composite. Also for RW, correlations are shown for the Wiles et al. (2014) RW based RCS reconstruction. Horizontal line denotes the 95% confidence limit. Correlations against individual months are presented in Supplementary Figure 2. **Right:** Varimax rotation principal component analysis results showing loadings of each chronology on each PC with an eigenvalue > 1.0. % values denote the explained amount of variance each PC explains of the original data input matrix.

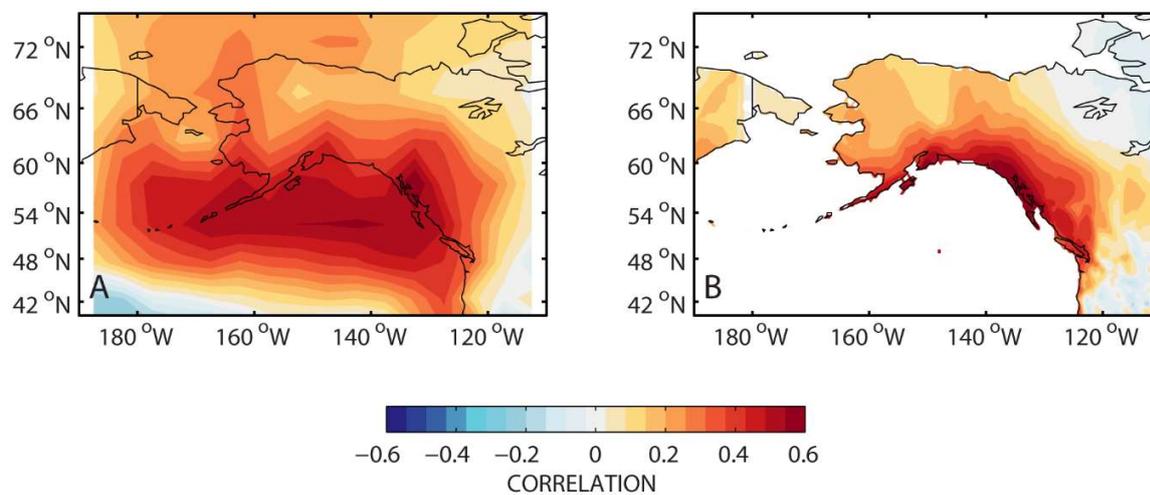
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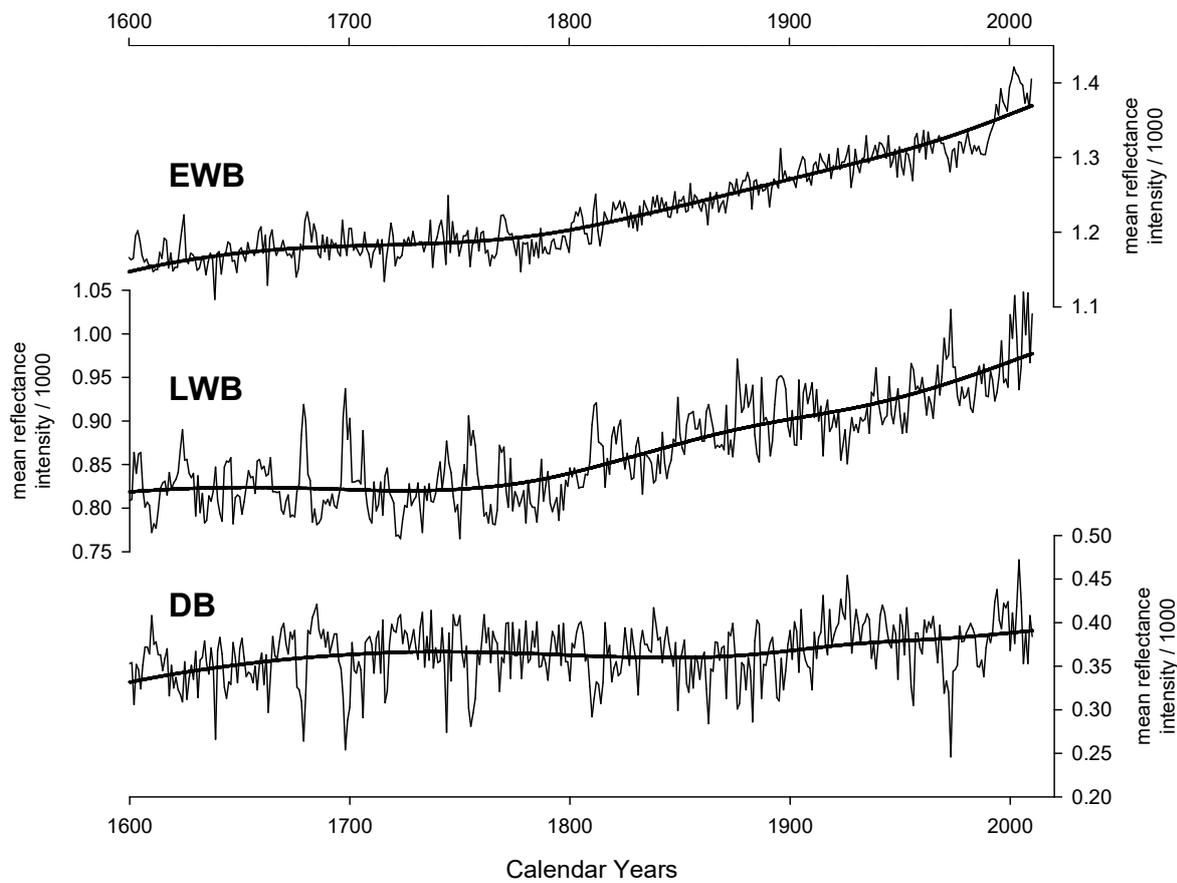
Figure 3: Illustration of the various PC regression experiments performed herein, with each reconstruction model compared against the June-September (Table 3). Feb-August is shown for RW as that was the reconstructed season in Wiles et al. (2014). Full period calibration is performed on the 1901-1989 period (Table 3 – CRU TS 3.2.4) while validation (Pearson’s correlation coefficient (r), Reduction of Error (RE) and

693 Coefficient of Efficiency (CE)) is undertaken over 1850-1900 using the BEST gridded data after those data
 694 were scaled to the CRU TS 3.24 data over the 1901-1989 period.
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 698 **Figure 4:** Spatial correlation (1901-1989) fields comparing the RW+DB GOA JJAS temperature reconstruction
 699 with larger-scale temperatures. **A:** for HADCRUT4 land/SST (Morice et al. 2012; Cowtan and Way 2014); **B:** for
 700 CRU TS3.24 land temperatures (Harris et al. 2012).

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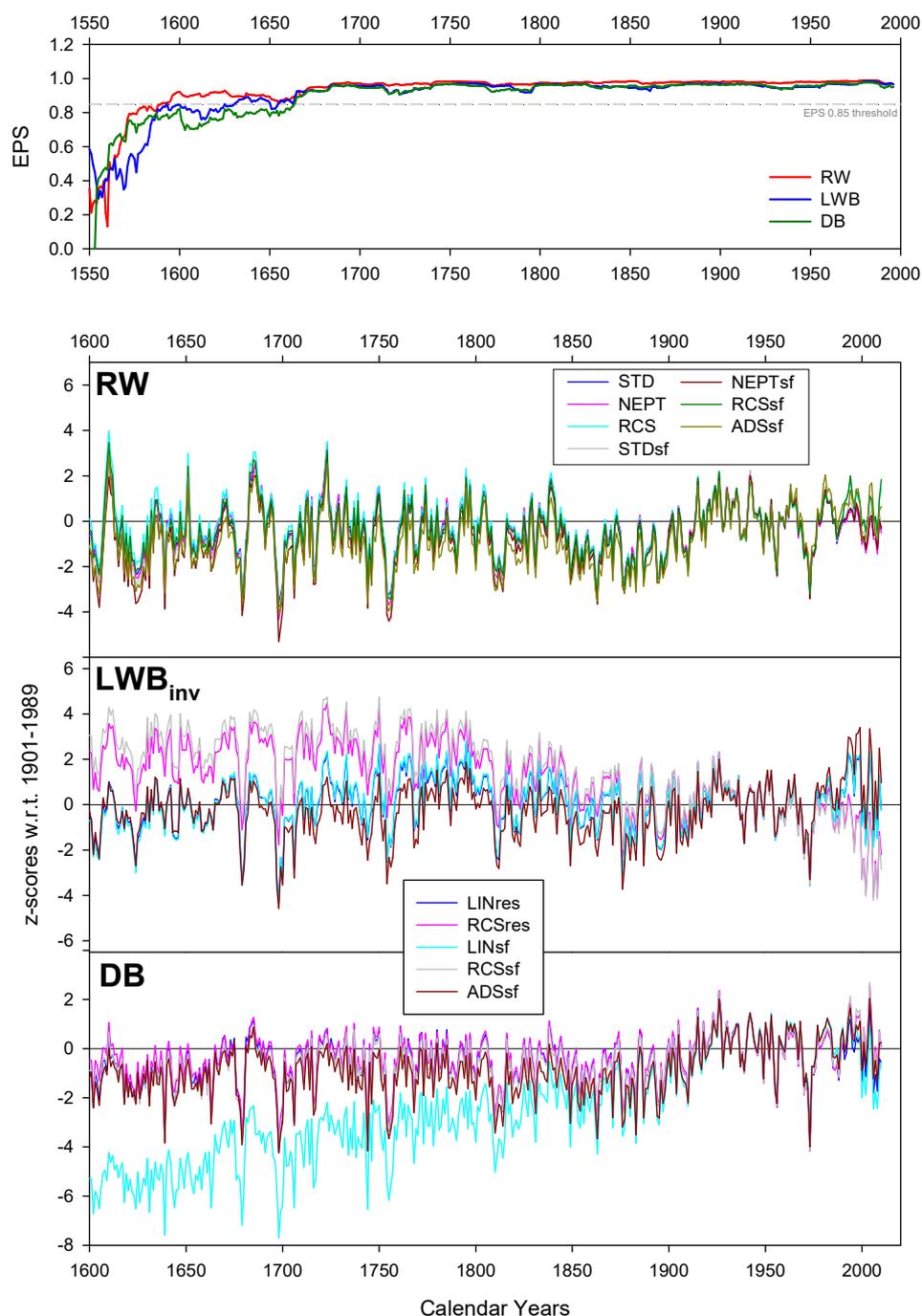


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705 **Figure 5:** Mean non-detrended GOA wide composite chronologies since 1600 for EWB, LWB (non-inverted) and DB. The
 706 LWB data have not been inverted for this figure.

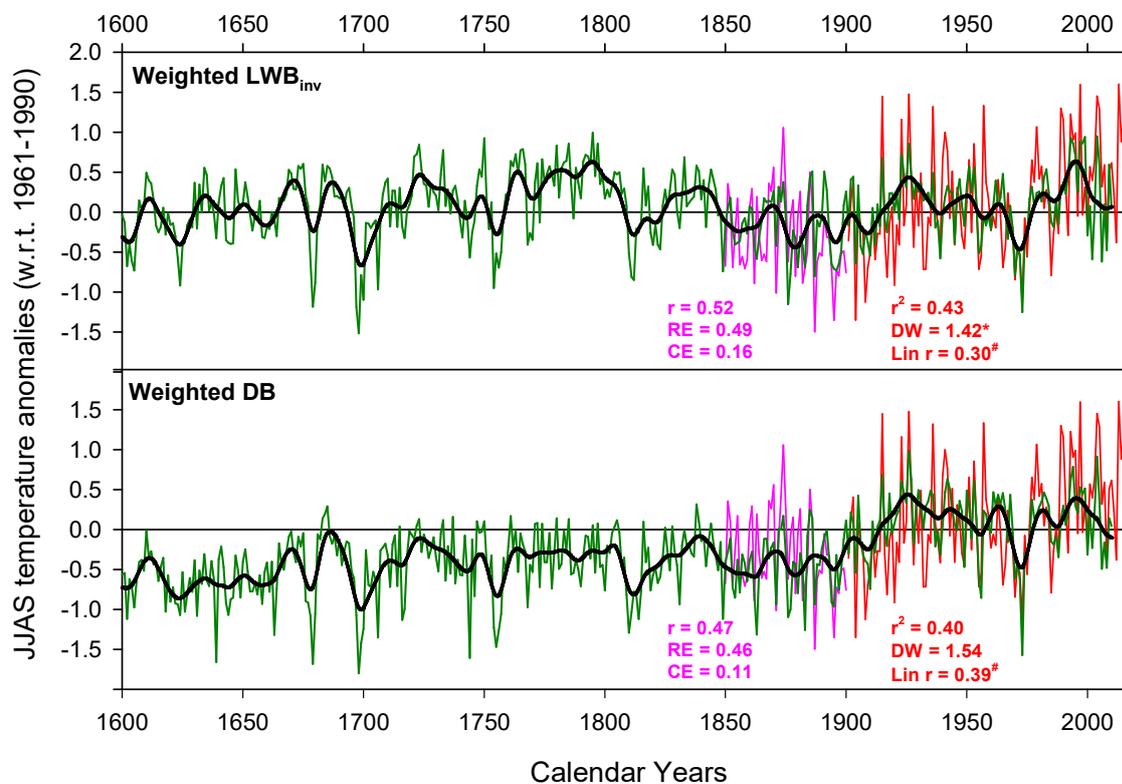
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Figure 6: Detrending experiments for each TR variable using the full GOA regional composite (data from all 8 sites). Upper panel is 31-year moving EPS plots for RW, LWB_{inv} and DB using 200-yr spline detrending. Lower set of plots present chronology variants from 1600-2010. For RW - STD = negative exponential detrending (ratio) or regression function of zero or negative slope; NEPT = as STD but raw data have been power transformed and detrended via subtraction; RCS = single group RCS detrending (ratio); STDsf, NEPTsf, RCSsf = as previous three options but using signal free detrending; ADSsf = Age dependent spline detrending using signal free. For LWB_{inv} and DB - LINres - detrending via subtraction using linear functions (negative or zero

717 slope); RCSres = as RCS above but detrending via subtraction; LINSf and RCSsf = as with LINres and RCSres
 718 but with signal free detrending; ADSsf = Age dependent spline detrending using signal free.

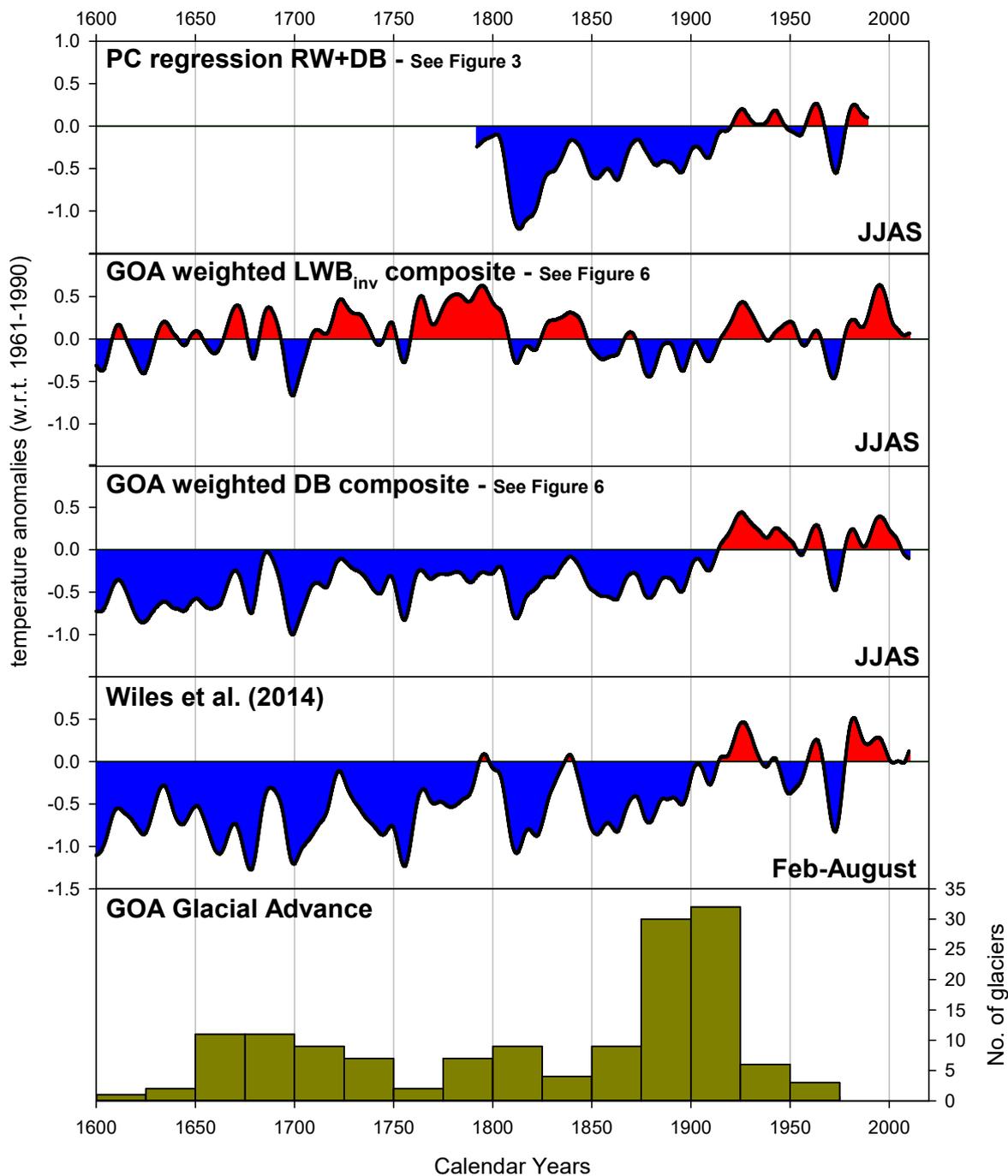


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721 **Figure 7:** Extended reconstruction tests using LWB_{inv} and DB regional weighted averages. 1901-2010 period
 722 calibration uses CRU TS3.24 data (red) while validation is performed using BEST data (pink) over the 1850-
 723 1900 period. * denotes significant 1st order autocorrelation in model residuals; # denotes a significant linear
 724 trend in the model residuals. The smoothed functions are 15-year cubic smoothing splines.

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728 **Figure 8:** Comparison of GOA reconstruction variants using DB and RW with Wiles et al. (2014). The lower
 729 panel presents a histogram of glacial advance in the GOA region (Wiles et al., 2004; Solomina et al. 2016).

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Site Name	Timespan	No. of series	Period n > 5	MSL	RW RBAR	EWB RBAR	LWB RBAR	DB RBAR	N-RW EPS	N-EWB EPS	N-LWB EPS	N-DB EPS
Juneau Mtn (JM)	1558-1998	17	1604-1998	238.5	0.35	0.15	0.24	0.25	10.7	32.9	17.7	17.3
McGinnis (MT)	1485-1999	15	1584-1999	363.5	0.47	0.11	0.24	0.24	6.4	46.3	17.6	18.0
Son of Repeater (SR)	1713-2009	10	1792-2007	216.7	0.33	0.12	0.17	0.25	11.3	43.5	27.5	17.4
Wright Mtn (WM)	1610-2010	17	1738-2010	234.2	0.45	0.06	0.25	0.17	6.9	84.0	17.1	27.9
Miners Well (MW)	1479-1994	13	1640-1995	324.0	0.49	0.05	0.33	0.14	5.8	120.3	11.8	36.2
Cordova Eyak Mtn (CVV)	1573-1992	17	1672-1992	280.6	0.46	0.15	0.32	0.29	6.5	32.1	12.0	14.2
Tebenkof (TBB)	1357-1990	15	1605-1990	339.2	0.43	0.13	0.20	0.22	7.6	37.9	22.4	19.6
Ellsworth (ELG)	1636-1991	18	1750-1990	218.5	0.40	0.14	0.24	0.29	8.6	35.7	17.7	14.2
			median	259.6	0.44	0.12	0.24	0.24	7.23	40.70	17.62	17.69

Table 1: Metadata information for the eight GOA sites used in the study. The sites are ordered from east to west (see Figure 1). All PCA and related analyses were performed on the 1792-1990 period for which there is replication for all eight sites of at least five series. Tree-ring data were detrended using a 200-year spline for these signal strength analyses. The final 4 columns denote the number of series needed to attain an EPS of 0.85 (Wigley et al. 1984).

RW	JM	MT	SR	WM	MW	CVV	TBB	ELG
1850-1900	0.45	0.22	0.49	0.22	0.27	0.30	0.30	0.38
1901-1990	0.49	0.26	0.42	0.41	0.36	0.41	0.20	0.34
1850-1990	0.50	0.37	0.47	0.43	0.39	0.47	0.33	0.39
LWB _{inv}	JM	MT	SR	WM	MW	CVV	TBB	ELG
1850-1900	0.45	0.29	0.48	0.38	0.49	0.40	0.25	0.46
1901-1990	0.52	0.39	0.64	0.58	0.46	0.45	0.28	0.41
1850-1990	0.37	0.32	0.55	0.46	0.53	0.51	0.33	0.44
DB	JM	MT	SR	WM	MW	CVV	TBB	ELG
1850-1900	0.45	0.29	0.49	0.23	0.35	0.40	0.37	0.48
1901-1990	0.57	0.45	0.58	0.47	0.48	0.50	0.23	0.39
1850-1990	0.53	0.44	0.48	0.38	0.44	0.52	0.34	0.44

Table 2: Correlations (1850-1900, 1901-1990 and 1850-1990) for each site RW, LWB_{inv} and DB chronology against JJAS temperatures. EWB correlations are not shown. The sites are ordered from east to west (see Figure 1).

mean r	RW	EWB	LWB _{inv}	DB
RW		0.27	0.68	0.81
EWB			-0.23	0.36
LWB _{inv}				0.80
DB				

Table 3: Correlation matrix between the different tree-ring variable chronologies (200-year spline detrended). These values represent the averages for between TR variable correlations performed separately for each site.

		1901-1960 Calibration			1961-1989 Validation			1901-1989 Full Calibration + Residuals			
Wiles14	season	series entered	r	r2	r	RE	CE	r	r2	DW	Linr
	MJJA	Wiles2014	0.60	0.36	0.48	0.11	0.10	0.55	0.30	1.62	0.15
	MJJAS	Wiles2014	0.55	0.30	0.53	0.21	0.20	0.53	0.28	1.72	0.17
	JJA	Wiles2014	0.58	0.34	0.47	0.06	0.05	0.53	0.28	1.75	0.17
	JJAS	Wiles2014	0.52	0.27	0.53	0.20	0.20	0.51	0.26	1.77	0.18
	Feb-Aug	Wiles2014	0.60	0.36	0.54	0.23	0.23	0.57	0.33	1.78	0.17
RW	season	PCs entered	r	ar2	r	RE	CE	r	ar2	DW	Linr
	MJJA	1, 2	0.60	0.34	0.40	0.03	0.03	0.52	0.26	1.60	0.21
	MJJAS	1, 2	0.56	0.29	0.46	0.15	0.14	0.52	0.25	1.70	0.23
	JJA	1, 2	0.58	0.31	0.42	-0.01	-0.02	0.51	0.24	1.74	0.23
	JJAS	2, 1	0.53	0.26	0.49	0.16	0.15	0.51	0.24	1.76	0.24
	Feb-Aug	2, 1	0.60	0.36	0.46	0.08	0.08	0.54	0.27	1.75	0.23
LWB_{inv}	season	PCs entered	r	ar2	r	RE	CE	r	ar2	DW	Linr
	MJJA	1, 2	0.63	0.38	0.49	0.15	0.14	0.57	0.31	1.39	0.20
	MJJAS	1, 2	0.63	0.37	0.55	0.23	0.22	0.59	0.34	1.50	0.23
	JJA	1, 2	0.71	0.49	0.58	0.16	0.15	0.66	0.42	1.45	0.25
	JJAS	1, 2	0.69	0.46	0.64	0.27	0.27	0.66	0.43	1.51	0.27
DB	season	PCs entered	r	ar2	r	RE	CE	r	ar2	DW	Linr
	MJJA	1, 2	0.69	0.45	0.43	-0.01	-0.02	0.59	0.33	1.55	0.24
	MJJAS	1, 2	0.67	0.43	0.50	0.09	0.08	0.61	0.37	1.68	0.26
	JJA	1, 2	0.70	0.47	0.50	-0.05	-0.05	0.62	0.36	1.65	0.26
	JJAS	1, 2	0.68	0.44	0.58	0.11	0.11	0.63	0.38	1.72	0.29
RW + LWB_{inv}	season	PCs entered	r	ar2	r	RE	CE	r	ar2	DW	Linr
	MJJA	1, 2	0.69	0.45	0.46	0.03	0.03	0.60	0.34	1.67	0.18
	MJJAS	1, 2	0.66	0.43	0.51	0.13	0.12	0.62	0.37	1.87	0.20
	JJA	1, 2, 3	0.72	0.49	0.52	-0.07	-0.08	0.63	0.37	1.56	0.26
	JJAS	1, 2, 3	0.68	0.43	0.59	0.12	0.12	0.63	0.38	1.63	0.28
RW + DB	season	PCs entered	r	ar2	r	RE	CE	r	ar2	DW	Linr
	MJJA	1, 2	0.71	0.49	0.44	-0.16	-0.16	0.62	0.36	1.69	0.04
	MJJAS	1, 2	0.72	0.51	0.49	-0.14	-0.15	0.61	0.36	1.78	-0.11
	JJA	1, 2, 3	0.72	0.50	0.49	-0.15	-0.15	0.56	0.32	1.89	-0.12
	JJAS	1, 2	0.71	0.49	0.52	-0.18	-0.18	0.64	0.39	1.84	0.05

Table 4: Calibration experiments for the four strongest seasons (see Figure 2). Initial calibration (using CRU TS 3.24) was made over 1901-1960 and validation over 1961-1989. Full calibration (1901-1989) was also performed to allow for residual tests and extra validation using BEST (1850-1990 – see Figure 2). Shaded results do not pass significance. r = Pearson's correlation coefficient; r_2 = coefficient of determination; ar_2 = r_2 adjusted for the number of predictors in the model; RE = Reduction of Error; CE = Coefficient of Efficiency; DW = Durbin-Watson test for residual autocorrelation; LINr = linear trend of the residuals.

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		1901-2010 Calibration				1850-1900 Validation			
		series entered	r	r2	DW	LINr	r	RE	CE
LWB_{inv}	LINres	0.64	0.41	1.36	0.36	0.53	0.44	0.07	
	RCSres	0.26	0.07	1.28	0.48	0.56	0.01	-0.64	
	LINsf	0.64	0.41	1.37	0.36	0.53	0.43	0.06	
	RCSsf	0.21	0.05	1.32	0.46	0.56	-0.05	-0.73	
	ADSsf	0.69	0.47	1.58	0.06	0.50	0.51	0.20	
		1901-2010 Calibration				1850-1900 Validation			
		series entered	r	r2	DW	LINr	r	RE	CE
DB	LINres	0.55	0.31	1.37	0.50	0.50	0.52	0.21	
	RCSres	0.64	0.40	1.59	0.40	0.48	0.50	0.18	
	LINSF	0.54	0.29	1.35	0.38	0.43	0.40	0.00	
	RCSsf	0.65	0.43	1.64	0.35	0.47	0.48	0.15	
	ADSsf	0.65	0.42	1.59	0.30	0.47	0.34	-0.09	

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Table 5: Extended reconstruction calibration experiments using different chronology versions (Figure 6) of LWB_{inv} and DB. Shaded results do not pass significance.

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