

# 1 An empirical resampling method for determining optimal high-pass filters used in 2 correlation-based tree-ring crossdating.

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## 7 Abstract

8 Visual crossdating of tree-ring series focusses on high-frequency variations. Automated correlation-based  
9 crossdating tools mimic this by transforming raw ring widths into indices that emphasise the high frequency  
10 signal, prior to calculating the goodness-of-fit between series. Here we present a resampling methodology to  
11 determine the relative merits of alternative simple high-pass filters and demonstrate it using two tree-ring  
12 data sets (British Isles oak, New Zealand kauri). Results indicate that: a) high-pass filtering is a critical step;  
13 b) the efficacy of alternative filters is variable, and; c) efficacy appears to be species specific. These results  
14 have implications for crossdating in the two contexts investigated, and also for future software developments,  
15 especially the desirability of flexible implementations of high-pass filtering.

16 *Key words:* dendrochronology, crossdating, oak, kauri.

## 17 1. Introduction

18 Visual crossdating may seem routine for a skilled and experienced dendrochronologist working on a familiar  
19 species. They are likely to have developed an intimate understanding of what a correct-date match looks  
20 like, and the ability to readily distinguish it from the multitude of mostly poor matches at misaligned positions.  
21 Some of the latter may occasionally be strong enough to warrant close examination and caution may lead to  
22 rejection of some date-aligned samples because the “goodness-of-fit” is too weak for confidence.  
23 Determining this goodness-of-fit may involve direct visual inspection of sample pairs under the microscope,  
24 or comparison of time series plots of ring widths, perhaps log-transformed or converted into derived indices.  
25 Alternatively, crossdating may use abstracted (i.e. reduced) information, such as A.E. Douglas’s skeleton  
26 plot technique (Speer, 2010). The specific approach used will be influenced by the dendrochronologist’s  
27 training and will probably evolve with experience and experimentation. Moreover, because visual pattern  
28 recognition is subjective, different dendrochronologists looking at the same data will inevitably assess  
29 goodness-of-fit somewhat differently.

30 Although there are diverse ways to visually compare temporal patterns, high-pass filtering is ubiquitous. This  
31 is explicit in the abstraction methods, where the derived series are essentially reduced to ring-width  
32 variations relative to a few adjacent rings (e.g. skeleton plotting), or perhaps first-order differences. It is  
33 implicit in other visual approaches where the researcher’s “view” of the sample is limited to a relatively short  
34 sequence at any particular point in time. In this case, although short-term trends may be taken into  
35 consideration, our experience is that it is always the high-frequency variation about that trend which is most  
36 important, especially notably wide and narrow rings, and sometimes sub-decadal signature patterns.

37 Notwithstanding the diversity of visual approaches to assessing goodness-of-fit, and the inherent subjectivity  
38 of associated pattern matching, a generic conceptualisation of the crossdating process is possible (Fig. 1).  
39 Consider the case of two time series being compared to each other at many overlapping positions. We know  
40 that all but possibly one of these overlap positions is misaligned and we expect to see mostly no or weak  
41 agreement between the series at these positions (the frequency curve in Fig. 1). Even if our assessment of  
42 goodness-of-fit is purely subjective we implicitly can assess some matches as “-ve”, denoting situations of  
43 disagreement (i.e. wide rings on one series mostly corresponding to narrow rings on the other), some as  
44 showing no meaningful association, and others as “+ve”. Because experience and a basic understanding of  
45 probability inform us that strong +ve matches at misaligned positions are rare, but possible, the experienced  
46 dendrochronologist is likely to impose some sort of goodness-of-fit threshold for what they will accept as  
47 possibly indicating a correct match. This threshold will necessarily be somewhat vague for subjective pattern  
48 matching and it is likely to evolve with experience in what correct matches look like for the material being  
49 investigated. Arrows “A–C” in Fig. 1 indicate three hypothetical date-aligned goodness-of-fit positions: “A” is  
50 a match likely to be rejected because it is weaker than the threshold (i.e. there is too much risk that it is a  
51 spurious chance match); “B” is a stronger-than-threshold match, but within the bounds of plausible  
52 misaligned relationships, and; “C” is the ideal case of a very strong match outside of any seen for misaligned  
53 cases.

54 Although subjective visual crossdating remains a fundamental component of crossdating, various attempts  
55 have been made to supplement it, and deal with the undesirable subjectivity, by deriving suitable objective  
56 statistics to measure goodness-of-fit. The first of these was B. Huber’s ‘*Gleichläufigkeit*’, developed in the  
57 1930s, which quantifies the percentage of years that two series conjointly increase or decrease (Dean, 1997)  
58 – essentially the sign of the first-order difference. The statistic also provided the first means for estimating the  
59 statistical significance of a particular match and was automated in the late 1960s (Eckstein, 1972). Shortly  
60 after, Baillie and Pilcher (1973, BP73 hereafter) presented the “Belfast Method” of statistical crossdating,  
61 which uses Pearson’s product-moment correlation coefficient as the goodness-of-fit statistic and Student’s *t*  
62 as a measure of statistical significance. In this case, goodness-of-fit is calculated on transformed indices,  
63 representing relative changes about the local level<sup>1</sup>.

64 Both *Gleichläufigkeit*, and especially the Belfast Method, can be viewed as attempts to objectively automate  
65 the concepts underpinning visual pattern matching. They are simplifications, that reduce a sophisticated  
66 approach, in which multiple threads of evidence can be synthesised (albeit subjectively), to a single objective  
67 statistic. From this perspective, they can be viewed as supplementary crossdating tools, suitable for  
68 identifying candidate matching positions that can then be explored in depth using the visual approach  
69 (Baillie, 1982). In this context an objective statistic is ideal, because it permits near-instant automated  
70 application that crudely mimics visual matching at many thousands of positions. Moreover, conjoint  
71 computer-based and visual crossdating is arguably a more sophisticated methodology, because it permits  
72 alternative high-pass filtering methods to be explored, some of which are beyond the scope of visualisation  
73 of raw ring widths.

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<sup>1</sup> Local level is a generic term for evolving time series trend, typically calculated using some form of moving window. The running average is one such. Others include the running median, splines, and digital filters. BP73 used a five-year running mean and calculated annual indices as natural logarithms of percentage change from the mean (Table 1).

74 Although the conceptual merits of the Belfast Method are widely accepted, including the desirability of high-  
75 pass filtering of raw ring-width data prior to calculating goodness-of-fit, specific implementation details related  
76 to filtering have been challenged. For example, Munro (1984) showed that crossdating efficacy is filter-  
77 dependent, and Wigley et al (1987) noted that running means are problematic, because they introduce  
78 phase distortions that increase the frequency of relatively high correlations at mismatched positions.  
79 Moreover, it seems likely that filter efficacy will be influenced by species-specific, and perhaps location-  
80 specific, characteristics of the ring-width series – such as the frequency of missing rings, autocorrelation, and  
81 heteroscedasticity. If so, then a high-pass filtering method that works well in one situation may be sub-  
82 optimal when applied elsewhere, resulting in weaker crossdating. More frequent false positives (mismatched  
83 positions flagged as statistically significant) and lower statistical significance for date-aligned matches,  
84 compared to results obtained using a superior filter, may be a consequence.

85 This research is based on the assumption that high-pass filters have variable efficacy. This variability may be  
86 inherent (some filters are simply better than others), and may also be species and/or place specific. In this  
87 context, our aim is to develop and demonstrate an empirical resampling method to objectively quantify the  
88 efficacy of alternative filters, based on the conceptualisation of crossdating presented in Fig. 1. We do this in  
89 the context of two tree-ring data sets: a) the British Isles oak archaeological sites database compiled by  
90 Fowler and Bridge (2015), and; b) the living trees subset of the New Zealand kauri data set (Boswijk et al,  
91 2014). Both data sets were built using, at least in part, the BP73 crossdating methodology, but they are  
92 sufficiently different in terms of their respective ring-width data and how BP73 has been applied to provide a  
93 useful contrast. We limit our investigation to five simple high-pass filters that are commonly used or could be  
94 easily implemented in crossdating software. Our results will have direct relevance to crossdating  
95 methodology in the two specific cases investigated, may indirectly facilitate high-pass filter selection in other  
96 cases, and will usefully inform future software developments related to computer-assisted crossdating.

## 97 **2. Data**

### 98 *Oak*

99 The British Isles oak database remains as it was used in Fowler and Bridge (2017), itself updated from that  
100 used in Fowler and Bridge (2015). It contains 2024 sites covering the 1000–2010 CE time period. Although  
101 not important in the current paper, sites from inner-London have been excluded as they are likely to contain  
102 timbers imported into the area from a wide hinterland. The site chronologies used are quite variable in the  
103 number of constituent timbers, ranging from as few as three timbers to over 50 in some cases. Most are  
104 either from living trees, or from standing buildings. The database will continue to grow and be refined and  
105 may thus change in subsequent publications.

### 106 *Kauri*

107 Kauri (*Agathis australis* (D.Don) Lindl) is a member of the Araucariaceae and the only *Agathis* species  
108 endemic to New Zealand. Kauri occurs naturally in the upper North Island with the southern limit at about  
109 38S. It was abundant in lowland forest from sea level to 300 m in Northland, Auckland and Waikato, and up  
110 to 700 m in parts of the Coromandel Range (Ecroyd, 1982) and tolerated a range of conditions from lowland  
111 bogs to ridge crests. Landscape change since human arrival in the 13<sup>th</sup> century has resulted in fragmented

112 forest patches, particularly from fire and logging during the 19<sup>th</sup> and early 20<sup>th</sup> century. Most large areas of  
113 kauri forest are now preserved as part of the conservation estate.

114 The trees are large, up to 30 m tall with a straight, thick trunk up to 3 m diameter (Ecroyd, 1982), and can  
115 achieve ages >1000 years. Longevity and preservation of kauri wood in bogs made kauri a focus for  
116 dendrochronological study for palaeoclimate reconstruction and forest ecology. Since the 1980s, a kauri tree-  
117 ring database has been developed at the University of Auckland from three sources of wood: modern (living)  
118 trees; archaeological (= historical) wood mostly from 19<sup>th</sup> century structures; and Holocene age subfossil  
119 kauri recovered from lowland bogs (swamp kauri). Most of this data are included in a master tree ring  
120 chronology spanning 2488 BCE – 2002 CE, with a low number of older floating subfossil kauri sequences  
121 and chronologies (Boswijk et al, 2014). Of relevance here, the modern chronology (AGAUm13) spans 734  
122 years (1269 – 2002 CE). It is derived from ring width data from 228 trees (565 radii) located at 18 sites  
123 distributed throughout the natural range of kauri. Series length is typically between 100 and 300 years, with a  
124 low number exceeding 300 years. Sample depth is at a maximum in about 1900 CE (>400 radii), steadily  
125 decreasing to <50 radii by 1500 CE.

126 Much of the chronology development carried out since 1999 was undertaken using the Belfast method,  
127 integrating statistical (e.g. BP73) and visual matching. Kauri has particular growth characteristics that can  
128 present challenges to dating. These include lobate growth, suppression episodes, and wedging resulting in  
129 locally absent rings. False rings can occur but wholly missing rings are rare. Because issues such as locally  
130 absent rings affect outcomes from automated crossmatching, visual matching using line plots has been  
131 important to reconciling ring series as well as checking suggested matches.

### 132 **3. Methods**

#### 133 *High-pass filters*

134 Fig. 2a shows 101 years of mean oak ring-widths for Hengrave Hall and Abbey Farm, two East-Anglia  
135 archaeological sites, about 15 km apart. Both have a multi-decadal declining trend, similar decadal-scale  
136 patterns (except for about a 20-year period centred on 1460 CE), and inter-annual variability in close  
137 agreement. Figures 2b–d show the same data transformed using three high-pass filters: BP73 indices; first-  
138 order differences; and logged first-order ratios (Table 1: BP73, FOD, LBFOR). Each filter removes almost all  
139 of the decadal to multi-decadal trend, leaving residual high-frequency series that are visually and statistically  
140 in closer agreement than is the case for raw ring widths. The scatter diagrams (Panels e–h) show that high-  
141 pass filtering has much reduced the scatter, with variance explained ( $R^2$ ) by linear regression increasing from  
142 32% to 50–53%.

143 Although the three filters used in Fig. 2 have similar effects for the specific case shown, they are  
144 conceptually quite different. The BP73 method converts each ring width into a log-transform of its percentage  
145 size relative to the five years centred on that ring. Logged first-order ratios are similar, but measure relative  
146 change between adjacent rings. First-order differencing measures absolute width changes from one ring to  
147 the next. Under some circumstances the filters result in marked differences in the derived series. For  
148 example, ratio-based methods may be superior, in the sense of stronger agreement between correctly dated

149 series, if local variance depends on local level (heteroscedasticity), but they may be compromised if ring-  
150 widths become very narrow, because relative change is bounded low (zero) but not high.

151 In addition to the three high-pass filters shown in Fig. 2 we investigated two others (Table 1: D, LBR). Both  
152 involve fitting a binomial smoothing curve to the data, analogous to the BP73 running mean, then calculating  
153 indices as differences (D) or logged ratios (LBR) relative to the fitted curve. The alternative curve fitting was  
154 in response to the previously noted criticism of the running mean (Munro, 1984; Wigley et al 1987) and to  
155 allow experimentation with the flexibility of the fitted curve. Similarly, the implementation of the BP73 running  
156 mean filter was made flexible so that alternative window widths could be explored.

157 Each of the three ratio-based filters (BP73, LBR, LBFOR) includes a  $\log_e$  transform. This is partly for  
158 consistency with BP73, but also has the advantage of reducing the scope for extreme outliers where the  
159 fitted curve (LBR) or immediately preceding ring (LBFOR) is near zero. However, missing rings (kauri only)  
160 are a special case needing workarounds to avoid potential divide-by-zero and  $\log_e(0)$  errors. For consistency  
161 with how BP73 has been applied in the kauri case, the BP73 algorithm was not changed – instead missing  
162 rings were given a value of one. For the other two ratio-based filters, minimum and maximum ratio bounds  
163 were set prior to the  $\log_e$  transform, with 0.01 and 100 used as initial minimum and maximum values. In the  
164 rare case of multiple missing rings, zero divided by zero cases were set to  $\text{Log}_e(1)$ . Because the fitted  
165 binomial smoothing curve reaching zero is very rare (requiring a block of missing rings as long as the  
166 number of binomial filter weights), divide by zero issues are largely confined to the LBFOR filter.

#### 167 *Resampling methodology for assessing the merits of high-pass filters*

168 As noted above, the merits of different high-pass filters depend on the specific characteristics of the samples  
169 in question. It is possible that an optimal filter for one species may not be so for others, nor perhaps even for  
170 the same species under different growing conditions. However, for any specific case (e.g. British Isles oak or  
171 New Zealand kauri), we contend that an objective method of determining an optimal filter can be derived by  
172 random resampling at misaligned and date-aligned positions, provided that a large crossdated tree-ring  
173 database is available. In the context of Fig. 1, resampling of inter-series correlations at misaligned positions  
174 empirically defines the frequency distribution and permits formal definition of a suitable “threshold” (e.g. the  
175 0.999 quantile). Resampling of date-aligned correlations provides an analogous frequency distribution and  
176 the overlap of the two distributions indicates the efficacy of the high-pass filter. In short, a good filter will  
177 minimise the spread of the misaligned distribution (especially the right tail) and maximise the separation of  
178 the two distributions. By increasing the percentage of date-aligned correlations to the right of the threshold  
179 quantile date-aligned matches are more likely to be flagged. The methodology is illustrated below, building  
180 from the Hengrave Hall case (Fig. 2) and expanding to the full British Isles oak database. Note that, because  
181 resampling is for fixed window widths, significance can be determined from the frequency distribution of  
182 correlation coefficients.

183 The British Isles oak database has 906 sites with extant tree-ring data at 1450 CE, 315 of which have  
184 complete data for 1450–1500 (Fig. 3). Correlating BP73 indices for Hengrave Hall with each of these other  
185 sites gives a mean correlation of 0.31. Abbey Farm is the highest of these and there is a spatial pattern of  
186 declining correlations to the north and west. Because the Hengrave Hall series is 146 years long we can  
187 extend the analysis to 45 different 101 year windows, centred on 1417 through 1461. This brings in

188 additional candidate comparison sites to those shown in Fig. 3, but the latter drop out at about the same rate,  
189 giving approximately 14,000 potential (non-independent) inter-site date-aligned correlations. Fig. 4a shows  
190 bootstrapped correlation frequency distributions for these and for misaligned correlations (right and left  
191 curves respectively), the latter drawn from millions of potential combinations of sites and dates. Fig. 4b is an  
192 equivalent analysis for raw ring widths. Comparing the two sets of plots demonstrates three significant  
193 impacts of BP73 high-pass filtering:

- 194 a) The frequency distribution for misaligned correlations is now centred on zero and has a shape  
195 approaching the normal distribution.
- 196 b) The spread of the frequency distribution for misaligned correlations is reduced, therefore reducing  
197 the threshold for statistical significance.
- 198 c) The separation between the date-aligned and misaligned correlation frequency distributions is  
199 increased. This “right-shift” of the frequency distribution for date-aligned correlations (relative to  
200 misaligned) increases the proportion of correct dates distinguishable as statistically-significant  
201 matches<sup>2</sup>.

202 Extending the Hengrave Hall analysis to all sites across the full oak database permits random sampling of  
203 several million date-aligned pairs and many times that number of misaligned pairs. Fig. 5a shows bootstrap  
204 correlation frequency distributions for unfiltered data with fixed series lengths of 101 years at misaligned and  
205 date-aligned positions. The former is derived from one million random pairs and the vertical dashed line in  
206 Fig. 5a is the associated 0.999 quantile ( $R = 0.793$ ). The distribution for date-aligned pairs is derived from  
207 10,000 pairs and the shaded area beneath the right tail of the curve denotes date-aligned correlations  
208 greater than the 0.999 quantile for misaligned positions. Fig. 5b shows comparable results for fixed series  
209 lengths of 51 years. Here we adopt the percentage of date-aligned correlations greater than the 0.999  
210 quantile for misaligned positions as our statistic for high-pass filter efficacy (Filter Efficacy Score, FES), with  
211 the results for unfiltered data providing baseline FES against which the performance of high-pass filters can  
212 be compared. For the inter-site oak case discussed here this is less than one percent for both series lengths  
213 tested. Fig. 5c,d shows the impact on FES of BP73 high-pass filtering. Note that right-shift is slightly higher  
214 for the shorter series (median 0.324 vs. 0.306), but the impact of this on the overlap of the respective  
215 frequency distributions is overwhelmed by conjoint changes in spread. This represents the familiar increasing  
216 difficulty of crossdating shorter sequences, because higher correlations are required for a correct match to  
217 emerge from the “background” of potential spurious (i.e. misaligned) correlations. All FES analyses  
218 undertaken here were repeated for series lengths of 51 and 101 years ( $FES_{51}$  and  $FES_{101}$  respectively) for  
219 each of the high-pass filters listed in Table 1, and for both the oak and kauri data sets.

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<sup>2</sup> The fact that date-aligned correlations for raw ring widths tend to be higher than correlations on BP73 indices in this case is not relevant to the right-shift argument, nor is it a characteristic feature when the analysis is extended to multiple sites. This Hengrave Hall result probably reflects the effect of the negative growth trend for the site (Fig. 2a). Because this is a characteristic tree-ring width series growth trend, raw ring-width correlations will have a positive bias at both date-aligned and misaligned positions.

## 220 4. Results & Discussion

### 221 Oak

222 Oak inter-site baseline  $FES_{51}$  and  $FES_{101}$  (i.e. for raw ring widths) are <1% (Fig. 5a,b). This means that very  
223 few correlations of date-aligned raw ring widths will be statistically significant against the background of  
224 random correlations at misaligned positions. BP73 high-pass filtering markedly improves this situation. Most  
225 importantly, the spread of the frequency distribution for correlations at misaligned positions is much reduced,  
226 with an associated reduction in the 0.999 quantile correlations, from about 0.8 (Fig. 5a,b) to less than 0.5  
227 (Fig. 5c,d). Similar reduction in spread of the date-aligned correlations results in a separation of each pair of  
228 frequency distributions, with an associated increase in the percentage of statistically significant date-aligned  
229 correlations. The percentage increases with series length.

230 As previously noted, one of the criticisms of the BP73 approach is that the five-year running mean is a  
231 suboptimal high-pass filter (Munro, 1984; Wigley et al., 1987). To investigate this, we compared running  
232 means to binomial filters with a similar approach of logging relative changes in ring width about the local level  
233 (LBR in Table 1). Multiple running window widths were investigated for each filter. Solid lines in Fig. 6 show  
234 filter efficacy scores for running mean windows of width 3–15 years, and for series lengths of 51 and 101  
235 years. Dashed lines show equivalent results for the LBR filter, where window width refers to the number of  
236 filter weights. Two results are noteworthy. First, five years is confirmed as the optimal window width for  
237 BP73. Second, the LBR filter is clearly superior, with efficacy highest at seven filter weights. Comparing  
238 detailed results for the latter (Fig. 7) with those for BP73 (Fig. 5c,d) indicates that the improved performance  
239 is almost entirely due to the reduced spread of the frequency curve for misaligned correlations, with no  
240 meaningful change in the right shift. In short, the poorer BP73 performance is caused by a higher frequency  
241 of spurious high correlations at misaligned positions (e.g. 44% more correlations greater than 0.3 for series  
242 lengths of 101 years).

243 Efficacy scores for the other high-pass filters are plotted against the right axis of Fig. 6. It is noteworthy that  
244 the difference-based filters (FOD, D) are generally poorer performers than the relative change ones (BP73,  
245 LBR, LBFOR), especially for the 101-year series length, provided that the optimal window width is used for  
246 the first two of these. Of the three relative-change filters, LBFOR achieves the highest efficacy scores for  
247 both series lengths investigated. This suggests that, for British Isles oak, relative change from one ring to the  
248 next, rather than variation about the local level, is marginally optimal for inter-site crossdating.

249 The inter-site analyses above were repeated, but this time correlating site chronologies against the all-site  
250 British Isles master. In this case baseline FES values are higher ( $FES_{51} = 21\%$ ,  $FES_{101} = 14\%$ ), due to less  
251 decadal-scale trend in the master chronology compared to individual sites. Results for each of the high-pass  
252 filters are shown in Fig. 8 and detailed results for one of the strongest (9-weight LBR) are given in Fig. 9. The  
253 most obvious difference between these and the inter-site results (Fig. 6, Fig. 7) is the more than doubling of  
254 the FESs, caused by the enhanced right-shift of the date-aligned correlations. The frequency distributions for  
255 correlations at misaligned positions are essentially identical to those for the inter-site analyses and the right-  
256 shift enhancement is simply a consequence of the stronger common signal in the master chronology due to  
257 massive replication. Inter-comparison of the BP73 and LBR filters (Fig. 8) gives very similar results to the  
258 inter-site analysis (Fig. 6). The LBR filter is again superior to BP73, although the difference is smaller in this

259 case. The optimal number of weights for the binomial smoothing curve is greater than indicated by the inter-  
260 site results, but is also less clear-cut. Nine to eleven weights appear to be the best choice, but sensitivity is  
261 low. The LBFOR filter again performs well, but is no longer clearly differentiated from other options. In fact,  
262 although all of the alternative filters perform better than BP73, there is little to differentiate between them,  
263 and improvements over BP73 are relatively small (0.3–4.3% increases in FES).

264 The results presented here confirm and quantify the importance of high-pass filtering for correlation-based  
265 oak crossdating. Without it, a statistically significant inter-site dating match will be extraordinarily rare (Figure  
266 5a,b). BP73 high-pass filtering improves the situation significantly (Fig. 5c,d), but alternative simple filters,  
267 especially those based on relative changes in ring width, generally perform better (Fig. 6, Fig. 8). Although  
268 incremental improvements over BP73 are fairly small, they are not trivial. For example, comparing BP73 to  
269 LBFOR for typical series lengths of about 100 years, the latter would correctly flag about 14% more date-  
270 aligned inter-site correlations as statistically significant<sup>3</sup>. The increase is only 2% in the site vs. master case,  
271 in part because BP73 FES<sub>101</sub> is already high (91.6%).

## 272 *Kauri*

273 The results reported above are specific to British Isles oak site chronologies, and applicability to other  
274 species, to other regions, and to non-site chronologies cannot reasonably be assumed. This is because  
275 different species in different environments may have characteristics (e.g. the frequency of missing rings) that  
276 influence which high-pass filter is optimal. To investigate this we investigated how the various high-pass  
277 filters perform in the case of New Zealand kauri for the more challenging context of crossdating individual  
278 radii against a kauri master chronology. The additional challenge relates to kauri radii often having missing  
279 rings and also frequently exhibiting notable heteroscedasticity (Fowler, 2009). For the purpose of this  
280 experiment we analysed radii from living trees and crossdated them against the Boswijk et al (2014) mean  
281 ring width master chronology for living trees (AGAUM13, Section 2).

282 Fig. 10a shows the AGAUM13 mean ring-width chronology, with 19-weight binomial smoothing curve, for the  
283 period 1700–1900. Panel b shows ring widths for radius CAS018A for the same period, also with fitted curve.  
284 CAS018A has a fairly common ring-width pattern for kauri of declining trend with age, with an associated  
285 decrease in evolving variance (i.e. heteroscedasticity). There are several quite narrow rings in the last few  
286 decades, including a single missing ring at 1839. Other time series plots in Fig. 10 are CAS018A indices,  
287 calculated using the five high-pass filters in Table 1. BP73 uses the original 5-year running mean with the  
288 1939 ring changed to one, the D and LBR indices were calculated using the 19-weight binomial smoothing  
289 curve (discussed below), and the LBFOR and LBR indices were bounded by minimum and maximum ratios  
290 of 0.01 and 100. Scatter plots immediately to the right of each time series are indices for AGAUM13 (x-axis)  
291 plotted against CAS018A (y-axis), in each case using the same index calculation method used by the paired  
292 time series plot (e.g. Panel h is BP73 indices). The two additional scatter plots (Panels n, o) are additional  
293 LBFOR and LBR analyses with the tighter ratio bounds of 0.2 and 5 shown by the dashed lines in Panels e  
294 and g. Note that scatters are plotted over the full data range in each case, making visual comparison across  
295 plots potentially misleading. For example, the only difference between Panels k and n is the scaling of the  
296 two circled points.

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<sup>3</sup> BP73 FES = 38.0. LBFOR FES = 43.3. Percent increase =  $100 \times (43.3 - 38.0) / 38.0 = 13.9\%$



297 FES dependence on the running mean window width (BP73) and on the number of binomial smoothing  
298 curve weights (LBR) is shown in Fig. 11. As with oak (Figs. 6, 8), five years is the optimal window width for  
299 the BP73 method, although FES decline as the window width increases is much reduced. The optimal  
300 number of binomial weights is in the range 17–21, which is notably higher than for oak. Both results indicate  
301 that kauri sub-decadal trend provides some useful information for crossdating purposes. Comparing the 7-  
302 weight and 19-weight LBR results indicates that the higher FES of the latter is solely caused by reduced  
303 spread of correlations at misaligned positions. In other words, widening the high-pass filter window does not  
304 improve agreement at date-aligned positions, but it does reduce the frequency of statistically-significant  
305 correlations at misaligned positions. On this basis, a 19-weight binomial smoothing curve was adopted for  
306 the D and LBR indices (Fig. 10f,g).

307 Thin dotted lines in Fig. 11 show kauri LBR FES results with the same settings used for oak applied. In sharp  
308 contrast to the oak results (Figs. 6, 8), the LBR filter is not superior to BP73. Moreover, results for the  
309 LBFOR filter ( $FES_{51} = 54\%$ ,  $FES_{101} = 81\%$ ), one of the best for oak, are clearly inferior. Part of the  
310 explanation for the relatively poor performance of the alternative ratio-based filters (LBFOR, LBR) lies with  
311 how very narrow rings, especially missing rings, are handled. As noted in Section 3, logged ratio-based  
312 methods encounter issues with missing rings, which led to the bounded ratios approach adopted here. This  
313 was not important in the oak case because we were dealing with mean ring-width site chronologies with few  
314 near-zero values, but it is problematic for kauri because missing rings on radii are not uncommon. The  
315 nature of the problem is clear in the case of the 1839 missing ring in Fig 10. For all three ratio-based indices  
316 (BP73, LBFOR, LBR) the missing ring is a clear outlier, as is 1840 in the case of LBFOR. The net effect is to  
317 inflate correlations where missing or very narrow rings are aligned. For example, the linear regression  $R^2$  of  
318 0.20 for LBFOR indices (Panel i) reduces to 0.13 if the two circled outliers are removed. In response to this,  
319 different ratio bounds were explored, with a view to minimising the outlier effect. We explored maximum  
320 (minimum) ratio bounds from 1000 (0.001) to 5 (0.2), the latter assumed to be reasonable limits to the  
321 bounding band, because anything more restrictive would begin to clip non-zero rings (see Fig. 10e,g). In  
322 terms of the FES, performance monotonically improved as the ratio bounding band was reduced, down to  
323 the 5 (0.2) limits. Fig. 10n,o show the impact of imposing this limit on the CAS018A LBFOR and LBR indices  
324 (others are unaffected) and the heavy dashed lines in Fig. 11 show the improved LBR performance,  
325 compared to the wider 100 (0.01) ratio bounds. The higher revised LBR  $FES_{101}$  (91%) than BP73 (88%)  
326 appears to be almost entirely due to ratio bounding, which BP73 does not have.

327 The performance of the D, FOD, and LBFOR (with revised ratio bounds) high-pass filters are plotted against  
328 the right axis of Fig. 11. All three have lower FESs than LBR and both filters that deal only with changes from  
329 one year to the next have lower FESs than BP73. The latter is consistent with the argument that kauri  
330 crossdating benefits from a broader perspective than how growth in one year relates to growth in the last.  
331 Also interesting is the relatively good performance of the D filter. The fact that this is only marginally lower  
332 than LBR suggests that absolute changes about the local level may be as useful for crossdating as relative  
333 changes. This is a particularly interesting result because it seems likely that performance of the D high-pass  
334 filter is degraded by typical heteroscedasticity, i.e. variance of local width about the local level scales with the  
335 local level, in kauri ring-width time series (Fowler, 2009). The CAS018A FOD and D indices (Fig. 10d,f)  
336 illustrate this very well, with higher variance over the period 1700–1745 associated with higher local level  
337 (Fig. 10b). Rescaling the indices over this period to give a similar range to those after 1745 reduces the

338 scatter in Fig. 10l and increases the linear regression  $R^2$  from 0.16 to 0.20. Note that ratio-based indices  
339 usually reduce heteroscedasticity (Fritts, 1976), but they often introduce “reversed” heteroscedasticity in the  
340 case of kauri, although this is usually less pronounced (Fowler, 2009; Fig. 10c,e,g).

341 In summary, the kauri data exposed a critical weakness of the ratio-based high-pass filtering methods in the  
342 presence of missing rings, highlighting the potential dangers of transferring methods to situations different to  
343 those in which they were developed. Ironically, the BP73 method, with the simple expedient of changing  
344 zeros to ones, proved relatively robust and one of the best performing indices until the ratio bounds were  
345 significantly tightened. In agreement with oak, high-pass filtering is again critical, but both the width of the  
346 filtering window and the optimal filter type differ. Kauri crossdating is best served by a slightly wider filter  
347 window and a simple difference-based filter shows promise.

## 348 **5. Summary and Conclusions**

349 The research presented here is framed in terms of computer-assisted crossdating, where automated  
350 correlation-based methods may usefully flag potential crossdating positions, but subsequent visual  
351 inspection of plots (and wood where possible) remains a fundamental requirement. In view of the time-  
352 consuming nature of the visual pattern-matching second stage, automation should ideally flag relatively few  
353 potential dating positions, with maximum likelihood that any correct date will be flagged. In terms of the  
354 conceptualisation of crossdating presented here, that means minimising the spread of the frequency  
355 distribution of correlations at misaligned positions (although actually it is only the right tail of the distribution  
356 that matters) and maximising separation of the distribution for date-aligned positions (what we have referred  
357 to as “right-shift”). The merit of high-pass filtering to achieve these ends is not in doubt, essentially mimicking  
358 the visual approach to crossdating, but our results usefully quantify how critical it is. Certainly, at the  
359 individual site (oak) and radii (kauri) levels, explored here, attempts to crossdate raw ring widths would  
360 clearly be a futile undertaking, with less than a 5% chance of date-aligned series being flagged as  
361 statistically significant.

362 Although high-pass filtering is clearly important, exactly what form of filter might be optimal is not obvious. A  
363 key part of our research was therefore to develop a resampling methodology that statistically approximates  
364 the conceptualisation of crossdating presented in Fig. 1, and provide a mechanism to objectively quantify the  
365 efficacy of alternative high-pass filters. We adopted the percentage of correlations at date-aligned positions  
366 above the 0.999 quantile of correlations at misaligned positions as our metric – the Filter Efficacy Score  
367 (FES). The relative merits of five simple high-pass filters were then determined by comparing FESs for  
368 identical resampling experiments.

369 The high-pass filters investigated here are all relatively simple. This is because our main focus was on  
370 developing the methodology for assessing the relative merit of filters (i.e. FES), but also because we thought  
371 it best to start with filters that are already implemented in existing crossdating software, or could be added  
372 relatively easily because they follow a similar approach. BP73 is commonly used, D and LBR follow the  
373 same approach of fitting a flexible smoothing curve, and FOD and LBFOR are very easy to implement. The  
374 mix also allowed comparison of filters based on relative changes (BP73, LBR, LBFOR) and absolute  
375 changes (D, FOD). Logging ratios was included in LBR and LBFOR for consistency with BP73 and bounding

376 of ratios was added to deal with issues related to missing rings. The use of a binomial smoothing curve in D  
377 and LBR instead of a running mean (BP73) was in response to statistical criticisms related to the latter. All  
378 five filters worked reasonably well, as initially implemented, when applied to the British Isles oak database,  
379 but significant issues related to missing rings emerged in the case of kauri. It was apparent that setting ratio  
380 bounding too high (e.g. 0.01, 100) resulted in outlier indices for missing rings, with highly undesirable  
381 impacts on the correlation frequency distributions, which in turn lowered FESs for the two ratio-bounded  
382 filters (LBR, LBFOR). This problem was solved by reducing the bounding range (to 0.2–5, Fig. 11).

383 For oak, our results indicate that LBFOR is the best performing filter overall, although only marginally so in  
384 some circumstances. For kauri, LBR appears to be best, but D is not far behind and perhaps may match  
385 LBR if heteroscedasticity is minimised using an approach similar to Cook and Peters (1997). Moreover,  
386 comparison of the oak and kauri results reveals some notable differences in the performance of the various  
387 high-pass filters. First, optimal window widths for the LBR (Figs. 6, 8, 11) and D filters are different for oak  
388 and kauri. The results for BP73 show comparable changes, although in this case the 5-year moving average  
389 window remains optimal. Second, the two filters that measure only changes from one year to the next (FOD,  
390 LBFOR) perform well for oak, but are poor candidates for kauri. Third, there are some notable differences in  
391 the performance of the relative change (BP73, LBR, LBFOR) and absolute change filters (D, FOD). The  
392 former are clearly superior for oak inter-site crossdating (Fig. 6), but not for kauri (although they still perform  
393 reasonably well).

394 The inter-species differences, noted above, demonstrate potential issues when transferring filters that have a  
395 proven track record for one species to another. It follows that a “one size fits all” approach to high-pass  
396 filtering is inappropriate and that detailed analysis is required to determine what will work best in different  
397 circumstances (e.g. Fig. 10). However, we think it important to stress that, as long as correlation-based  
398 crossdating is used as a precursor step to visual pattern matching, the main impact is likely to be to speed up  
399 the crossdating process. Although high-pass filtering is certainly critical, it appears that filter choice is a  
400 matter of refinement. At worst, using a sub-optimal filter will simply make the crossdating task somewhat  
401 more difficult, by increasing the frequency of false positives and reducing statistical significance associated  
402 with correct matches. Moreover, in practical terms, what can be achieved depends on how correlation-based  
403 crossdating is implemented in readily-available software. In that context, we encourage flexible coding that  
404 allow experimentation and fine tuning.

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432 **Figure captions**

433 **Fig. 1.** Conceptualisation of visual crossdating. Goodness-of-fit is the dendrochronologist’s subjective  
434 assessment of the agreement between two series being compared at multiple misaligned positions. Arrows  
435 “A”, “B”, and “C” denote possible date-aligned positions and “Threshold” is the, again subjective, standard  
436 required for a date to be considered plausible. Modified after Fowler and Bridge (2017).

437 **Fig. 2.** Hengrave Hall and Abbey Farm time series and cross-correlations (1400–1500). **a)** Simple ring-width  
438 plots. **b)** BP73 high-pass-filtered data: natural logs of ring widths expressed as percentages of the five years  
439 each ring is centred on (BP73). **c)** First-order differences (FOD). **d)** Natural logs of bounded first-order ratios  
440 (LBFOR). **e–h)** Scatterplots of the data in a–d, with linear regression lines and associated correlations.  
441 Details of high-pass filters are in Table 1.

442 **Fig. 3.** Correlation of Hengrave Hall (grey circle with black frame) BP73 indices with 314 other sites with full  
443 data available for the 101 years centred on 1450. Colour intensity shows correlation strength (see histogram)  
444 and the circle area (scaled to Students *t*) is a guide to statistical significance. The large circle northeast of  
445 Hengrave Hall is Abbey Farm (Fig. 2). Screen capture from *Oak Mapper* (Fowler & Bridge, 2015).

446 **Fig. 4.** Bootstrap (N=100,000) correlation frequency distributions for Hengrave Hall against other sites in the  
447 British Isles oak database at date-aligned and misaligned positions. **a)** BP73 indices. **b)** Raw ring widths.  
448 Series length (span) is fixed at 101 years.

449 **Fig. 5.** Oak inter-site bootstrap frequency distributions of correlations at misaligned (N=1,000,000) and date-  
450 aligned (N=10,000) positions. **a)** Unfiltered data and fixed series length (span) of 101 years. **b)** Unfiltered,  
451 span 51. **c)** BP73 filtered, span 101. **d)** BP73 filtered, span 51. Vertical dashed lines are empirically-derived  
452 0.999 quantiles ( $P = 0.001$ ) of correlations for the misaligned series. Shading denotes date-aligned  
453 correlations higher than the 0.999 quantile for correlations at misaligned positions – the Filter Efficiency  
454 Score (FES).

455 **Fig. 6.** Comparison of inter-site filter efficiency scores (percentage of all-site date-aligned correlations above  
456 the 0.999 quantile for misaligned correlations). Plotted values correspond to the shaded areas in Figure 5  
457 and are derived from analysis of identical all-site bootstrap (N=1,000,000) correlation frequency distributions  
458 for the British Isles oak database, for series lengths of 51 and 101 years. Solid lines are results derived using  
459 the BP73 high-pass filter method (BP73\_051, BP73\_101), but with variable running mean window widths.  
460 Dashed lines are equivalent results for logged bounded ratios, derived for a fitted binomial filter, where  
461 window width is the number of filter weights (LBR\_051, LBR\_101). Coloured bars on the right are results for  
462 three other high-pass filters: first-order differences (FOD\_051, FOD\_101); logged bounded first-order ratios  
463 (LBFOR\_051, LBFOR\_101); and differences relative to a fitted 7-weight binomial filter (D\_051, D\_101).

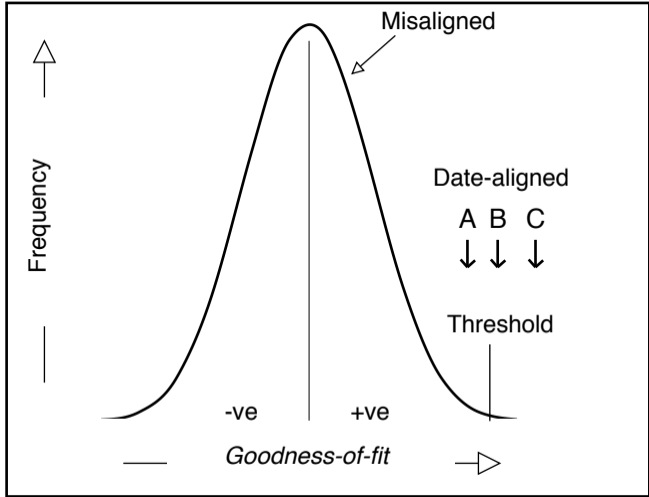
464 **Fig. 7.** Same as Fig. 5, for a 7-weight LBR high-pass filter (Table 1).

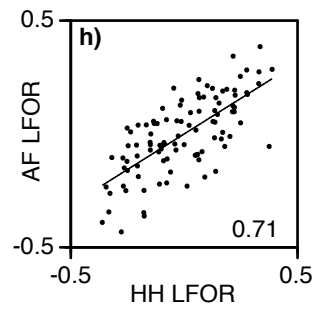
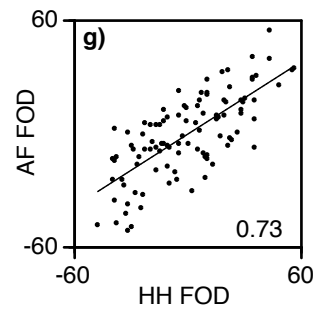
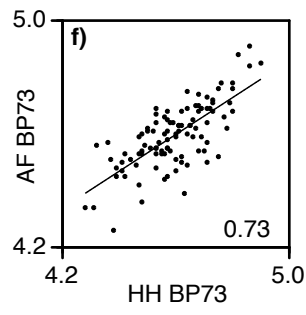
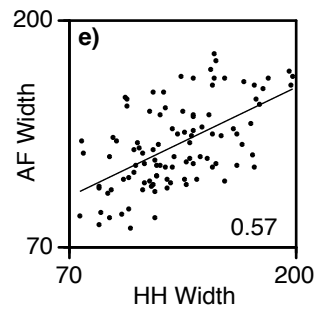
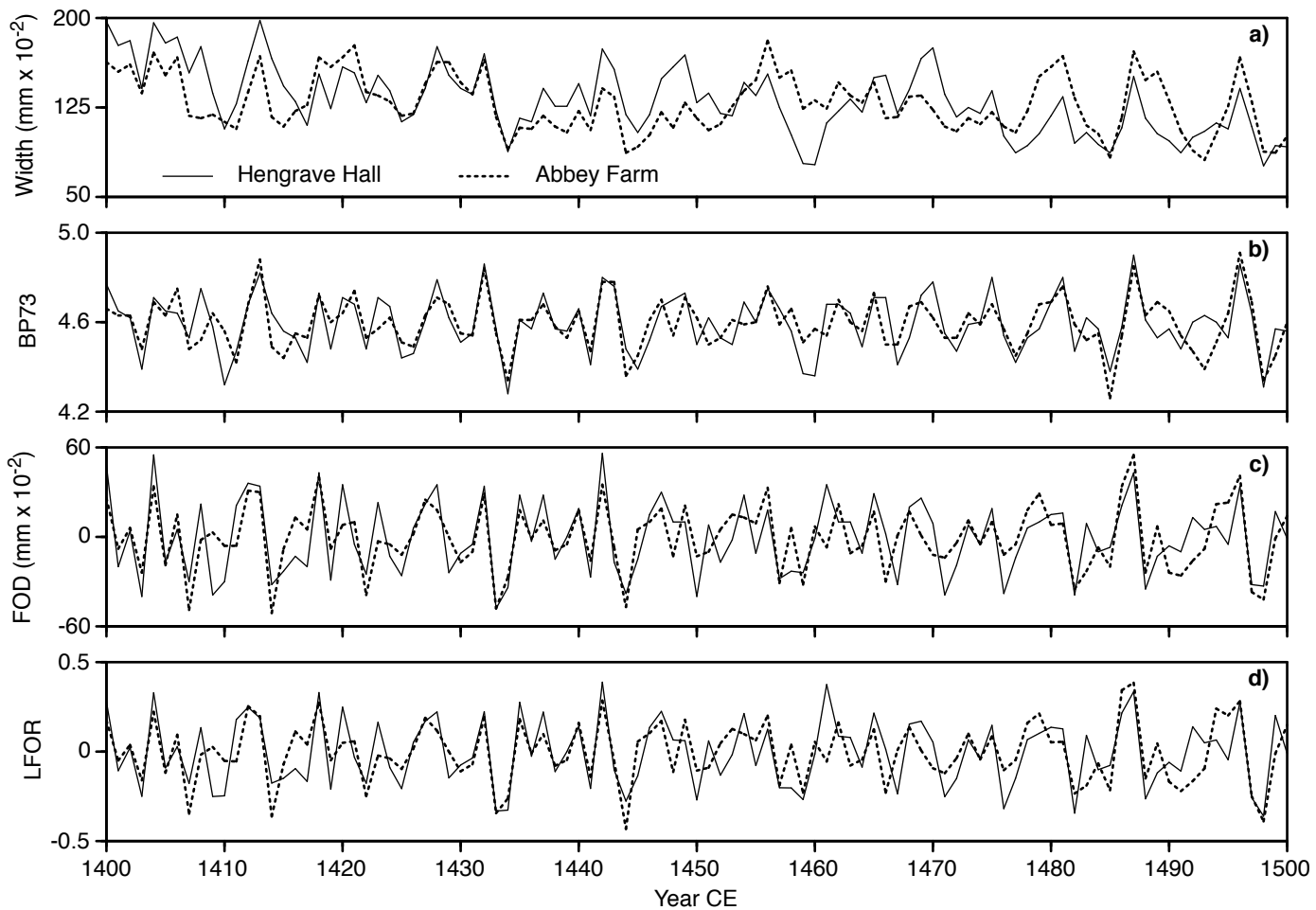
465 **Fig. 8.** Same as Fig. 6, for correlations between sites and an all-site British Isles master chronology.

466 **Fig. 9.** Same as Fig. 5c and 5d, for a 9-weight LBR high-pass filter and for correlations between sites and an  
467 all-site British Isles master chronology.

468 **Fig. 10.** Example of high-pass filter performance for kauri. **a,b)** Ring-width plots for AGAUm13 and radius  
469 CAS018A. **c–g)** CAS018A indices for the five high-pass filters (Table 1). Ratio bounds of 0.01 and 100  
470 applied to LBFOR and LBR. **h–m)** Scatter plots for CAS018A indices (y-axis) against AGAUm13 indices  
471 calculated in the same way. Linear regression lines are shown and the regression  $R^2$  is given in the bottom  
472 right corner of each plot. Circled data points are 1839 (missing ring) and 1840. **n,o)** Revised scatter plots for  
473 ratio bounds of 0.2 and 5.

474 **Fig. 11.** Same as Fig. 6 for Kauri radii-AGAUm13 cross-correlations. Thin dashed lines are LBR results for  
475 ratio bounds of 0.001 and 100. Heavy dashed lines are for revised ratio bounds (0.2, 5), as are LBFOR  
476 results.

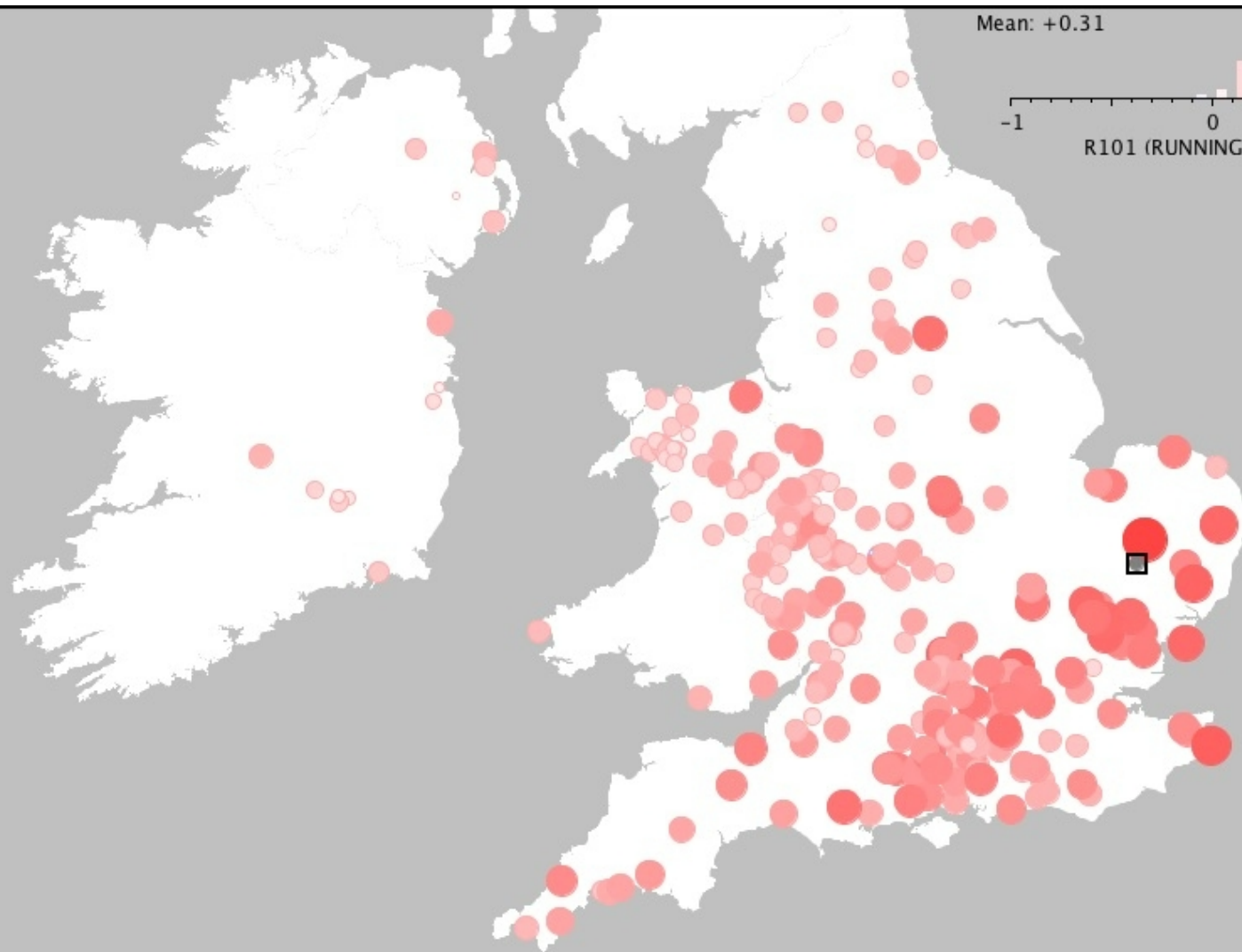
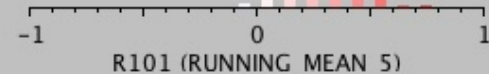




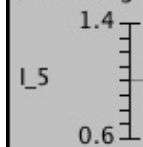
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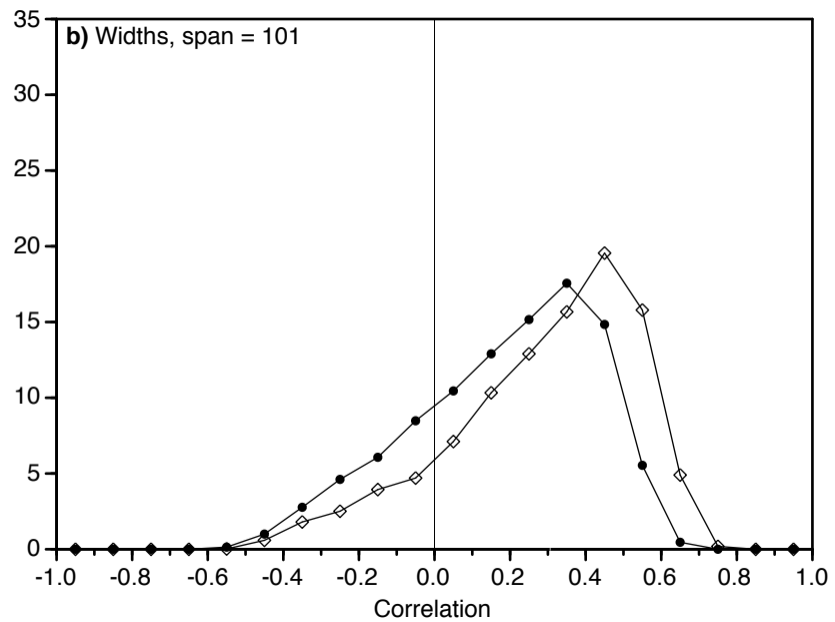
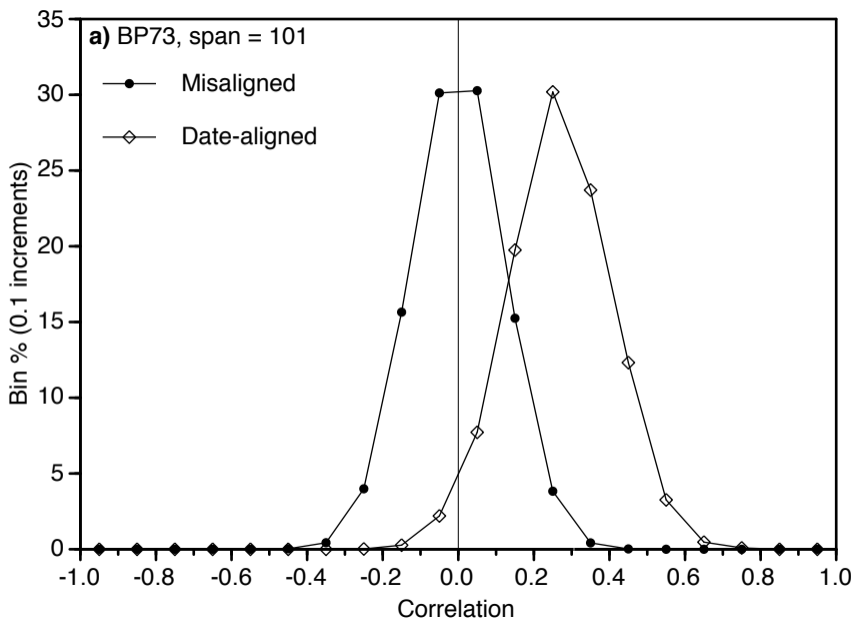
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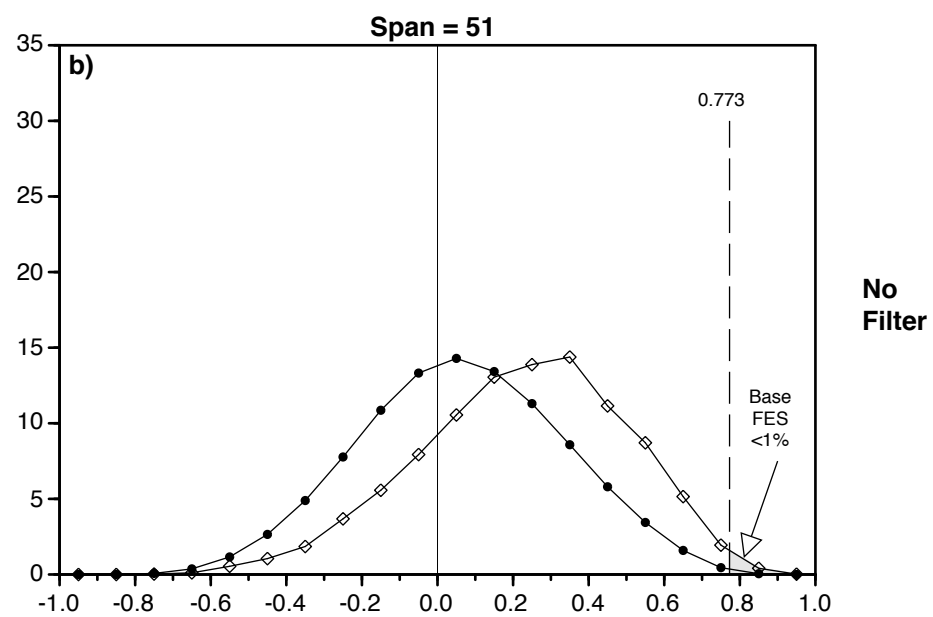
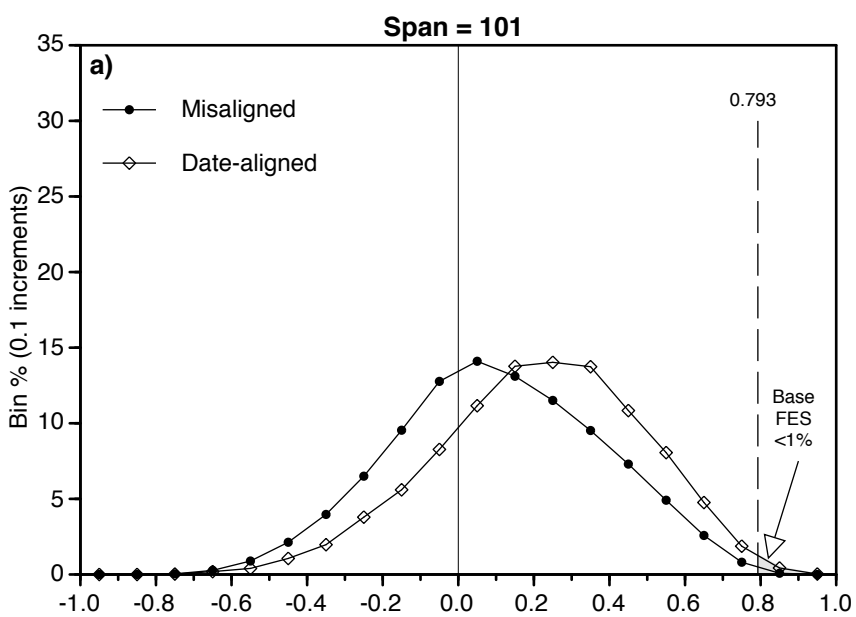


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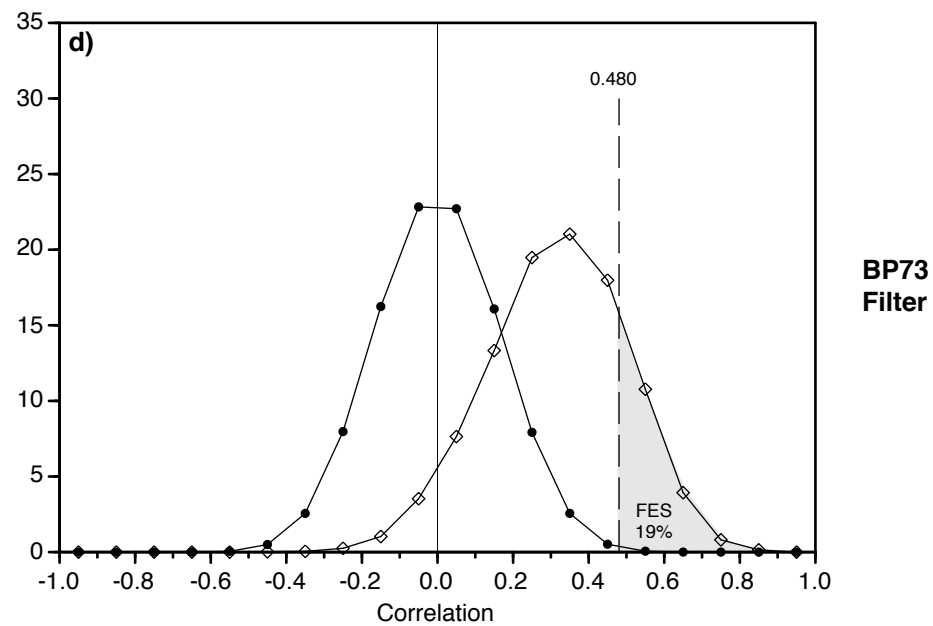
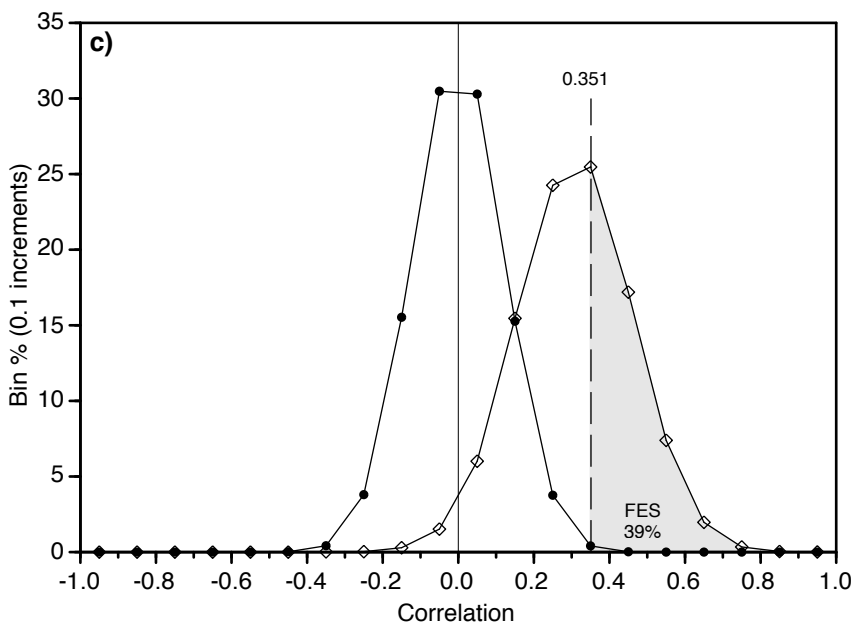




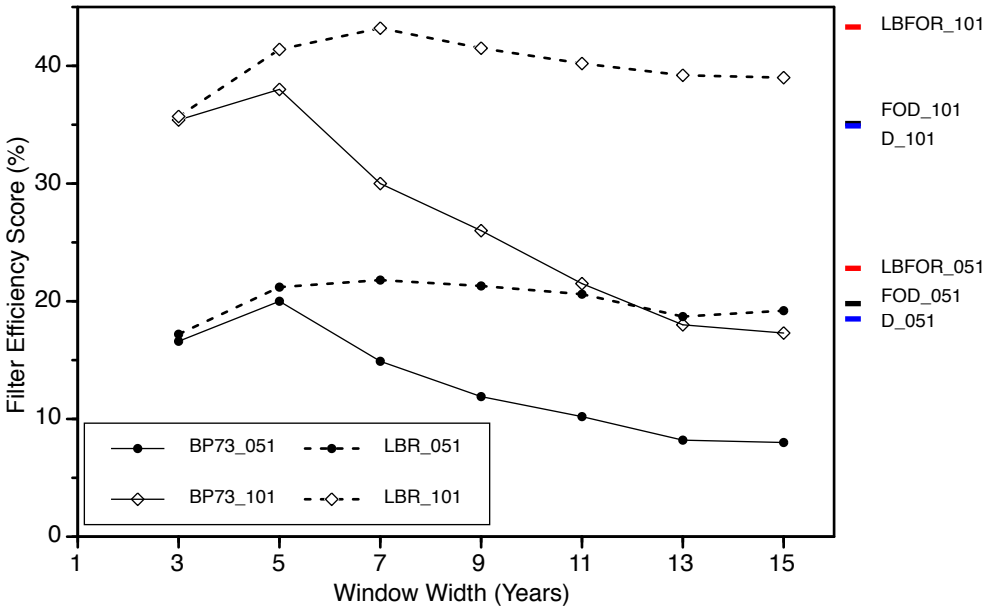


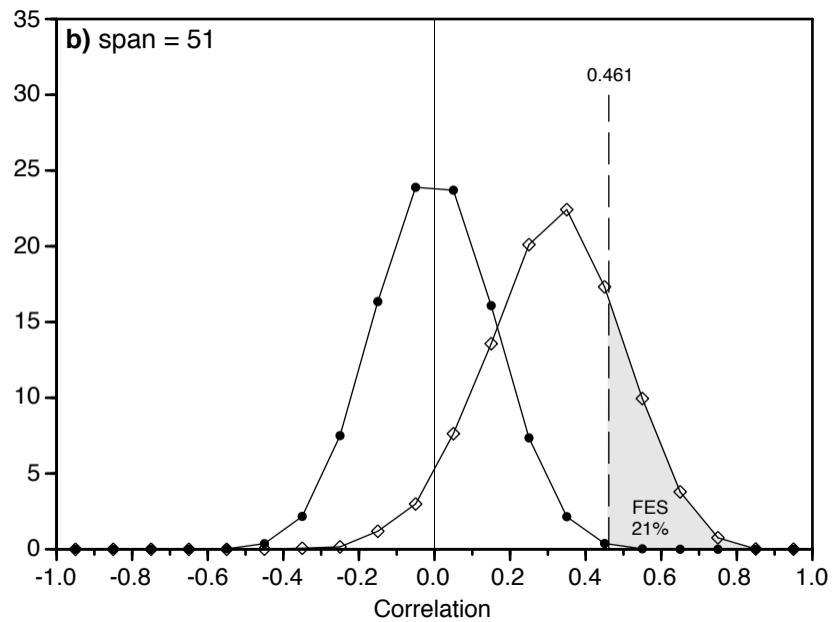
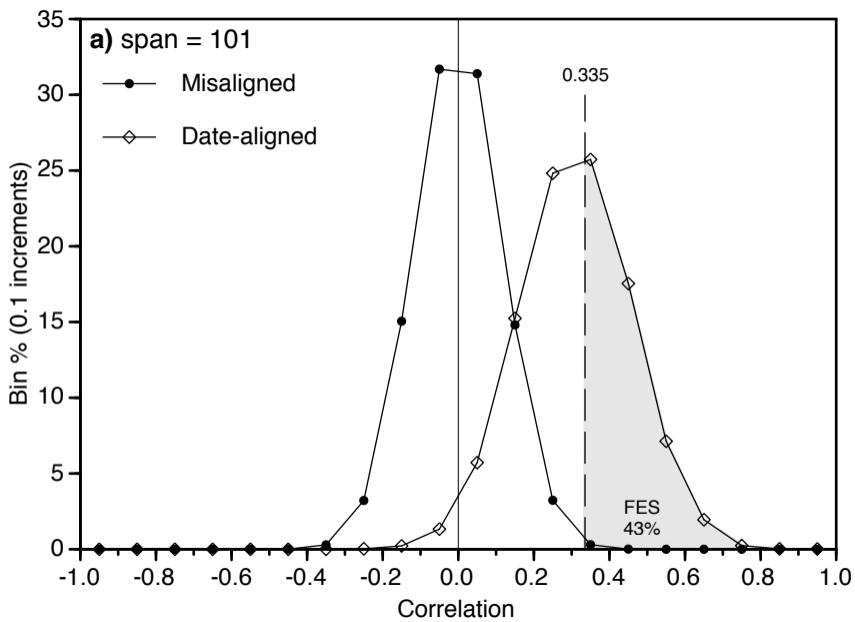


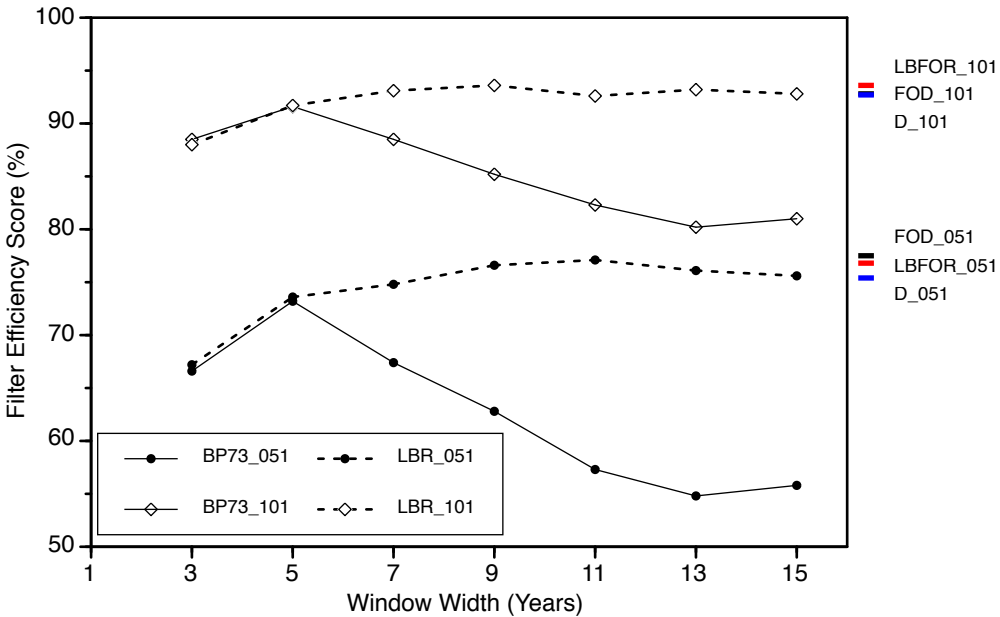
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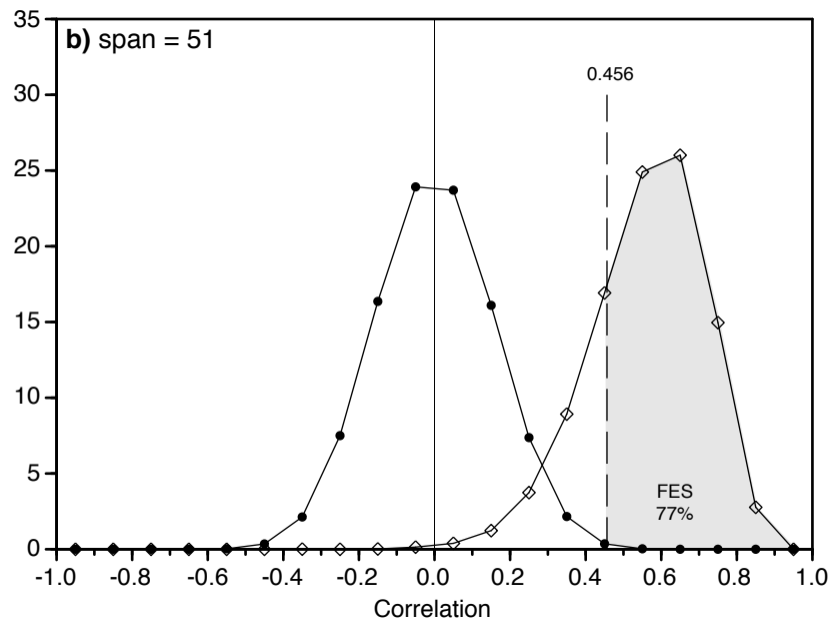
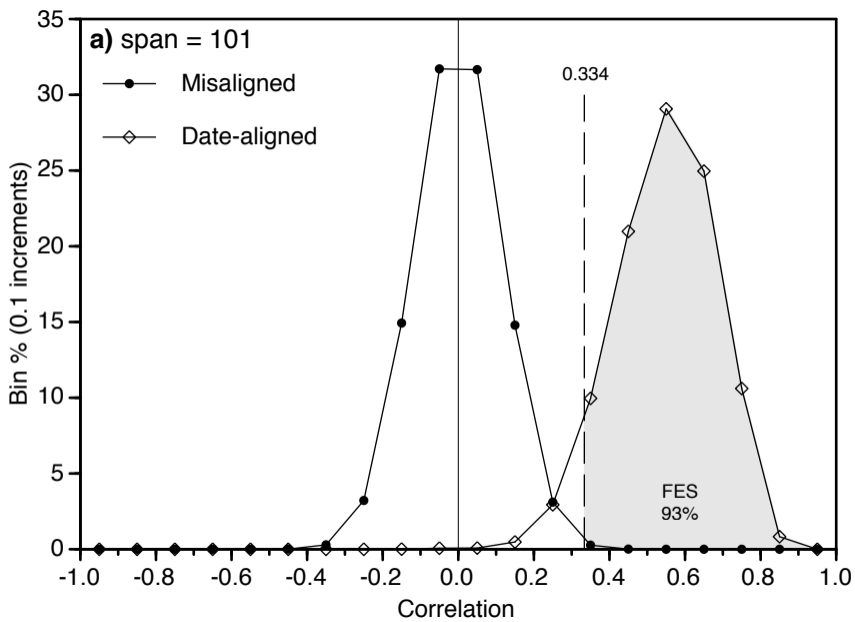


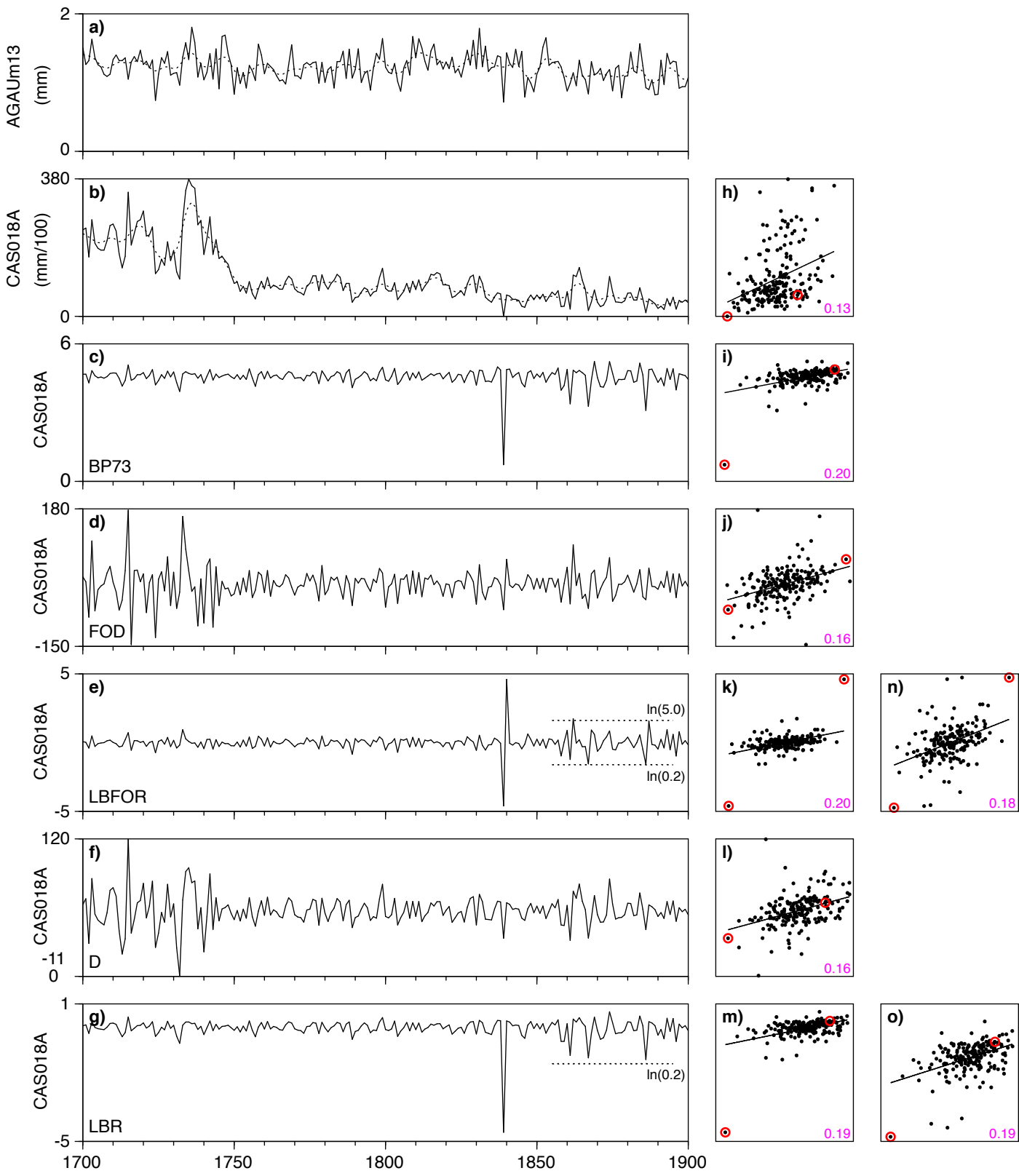
BP73 Filter

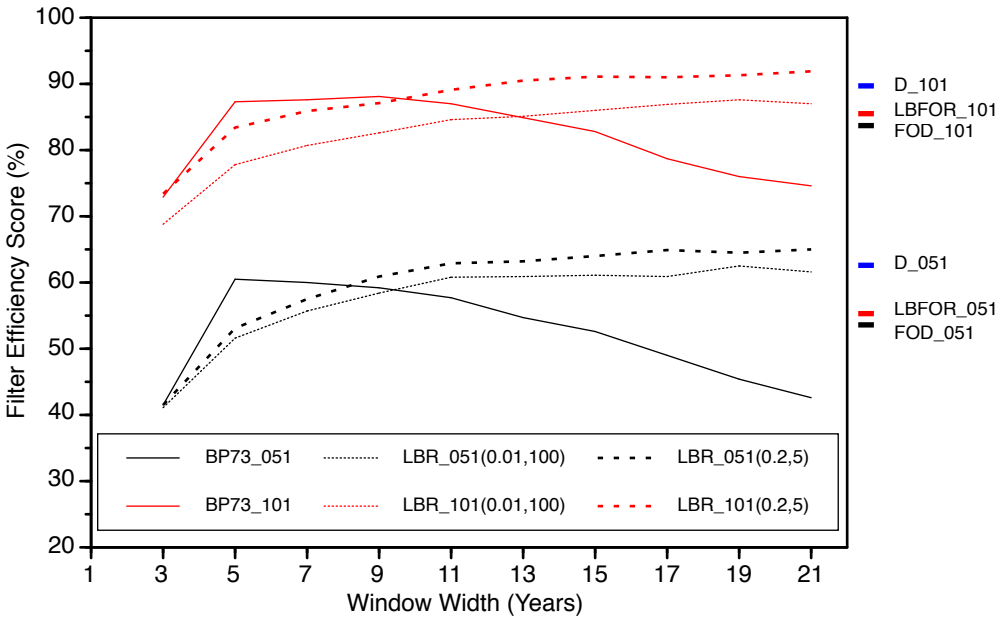














**Table 1.** High-pass filters.

Filter	Equations	Details
BP73	$I_i = \text{Log}_e\left(\frac{100 W_i}{RMk_i}\right)$ <p><b>if</b> (<math>W_i == 0</math>) <math>W_i = 1</math></p>	<p>Baillie and Pilcher (1973) method. <math>\text{Log}_e</math> of ring width (<math>W_i</math>) expressed as a percentage of the mean of the <math>k</math> years each ring is centred on (<math>RMk_i</math>). The running mean window width (<math>k</math>) is fixed at five years in the original BP73, but is adjustable in this implementation. Where <math>RMk_i</math> cannot be calculated, because the running-mean window extends beyond the end of the series, the first or last available running mean value is used. Zero rings are replaced by ones.</p>
FOD	$I_i = W_i - W_{i-1}$	<p>First-order differences. <math>I_0 = 0</math> (no change from unknown prior ring). Arrays are zero-indexed, making <math>I_0</math> the first element.</p>
LBFOR	$I_i = \text{Log}_e\left(\frac{W_i}{W_{i-1}}\right)$ $R_{min} \leq \frac{W_i}{W_{i-1}} \leq R_{max}$	<p><math>\text{Log}_e</math> of bounded first-order ratios. <math>I_0 = 0</math> (no change from unknown prior ring). <math>R_{min}</math> and <math>R_{max}</math> are <math>W_i/W_{i-1}</math> bounds (e.g. 0.01, 10), used to mitigate outliers and to avoid divide-by-zero and <math>\text{Log}_e(0)</math> math errors. If the denominator (<math>W_{i-1}</math>) is zero: <math>I_i = 0</math> if the numerator (<math>W_i</math>) is also zero, else <math>I_i = \text{Log}_e(R_{max})</math>.</p>
LBR	$I_i = \text{Log}_e\left(\frac{W_i}{BSCk_i}\right)$ $R_{min} \leq \frac{W_i}{BSCk_i} \leq R_{max}$	<p><math>\text{Log}_e</math> of bounded ratios. Ring widths dividing by the corresponding value from a <math>k</math>-weight binomial smoothing curve (<math>BSCk_i</math>). Where <math>BSCk_i</math> cannot be calculated, because the window extends beyond the end of the series, the first or last available value for the fitted curve is used. The number of smoothing curve weights (<math>k</math>) is flexible. Ratio bounding is as for LBFOR (above).</p>
D	$I_i = W_i - BSCk_i$	<p>Differences. Ring widths minus the corresponding value from a <math>k</math>-weight binomial smoothing curve (<math>BSCk_i</math>). End padding as for LBR (above).</p>