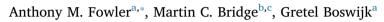
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## ORIGINAL ARTICLE

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



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## ABSTRACT

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

#### 1. Introduction

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

Although there are diverse ways to visually compare temporal patterns, high-pass filtering is ubiquitous. This is explicit in the abstraction methods, where the derived series are essentially reduced to ring-width variations relative to a few adjacent rings (e.g. skeleton plotting), or perhaps first-order differences. It is implicit in other visual

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http://dx.doi.org/10.1016/j.dendro.2017.04.003 Received 16 February 2017; Accepted 11 April 2017 Available online 24 April 2017 1125-7865/ © 2017 Elsevier GmbH. All rights reserved. approaches where the researcher's "view" of the sample is limited to a relatively short sequence at any particular point in time. In this case, although short-term trends may be taken into consideration, our experience is that it is always the high-frequency variation about that trend which is most important, especially notably wide and narrow rings, and sometimes sub-decadal signature patterns.

Notwithstanding the diversity of visual approaches to assessing goodness-of-fit, and the inherent subjectivity of associated pattern matching, a generic conceptualisation of the crossdating process is possible (Fig. 1). Consider the case of two time series being compared to each other at many overlapping positions. We know that all but possibly one of these overlap positions is misaligned and we expect to see mostly no or weak agreement between the series at these positions (the frequency curve in Fig. 1). Even if our assessment of goodness-of-fit is purely subjective we implicitly can assess some matches as "-ve", denoting situations of disagreement (i.e. wide rings on one series mostly corresponding to narrow rings on the other), some as showing no meaningful association, and others as "+ve". Because experience and a basic understanding of probability inform us that strong +ve matches at misaligned positions are rare, but possible, the experienced dendrochronologist is likely to impose some sort of goodness-of-fit threshold for what they will accept as possibly indicating a correct match. This threshold will necessarily be somewhat vague for subjective pattern matching and it is likely to evolve with experience in what correct matches look like for the material being investigated. Arrows "A-C" in







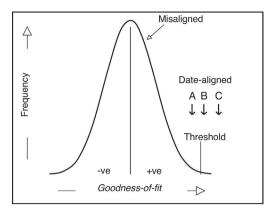


Fig. 1. Conceptualisation of visual crossdating. Goodness-of-fit is the dendrochronologist's subjective assessment of the agreement between two series being compared at multiple misaligned positions. Arrows "A", "B", and "C" denote possible date-aligned positions and "Threshold" is the, again subjective, standard required for a date to be considered plausible.

Modified after Fowler and Bridge (2017).

Fig. 1 indicate three hypothetical date-aligned goodness-of-fit positions: "A" is a match likely to be rejected because it is weaker than the threshold (i.e. there is too much risk that it is a spurious chance match); "B" is a stronger-than-threshold match, but within the bounds of plausible misaligned relationships, and; "C" is the ideal case of a very strong match outside of any seen for misaligned cases.

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

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

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

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

### 2. Data

#### 2.1. Oak

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

#### 2.2. Kauri

Kauri (*Agathis australis* (D.Don) Lindl) is a member of the Araucariaceae and the only *Agathis* species endemic to New Zealand. Kauri occurs naturally in the upper North Island with the southern limit at about 38S. It was abundant in lowland forest from sea level to 300 m in Northland, Auckland and Waikato, and up to 700 m in parts of the Coromandel Range (Ecroyd, 1982) and tolerated a range of conditions from lowland bogs to ridge crests. Landscape change since human arrival in the 13th century has resulted in fragmented forest patches, particularly from fire and logging during the 19th and early 20th century. Most large areas of kauri forest are now preserved as part of the conservation estate.

The trees are large, up to 30 m tall with a straight, thick trunk up to 3 m diameter (Ecroyd, 1982), and can achieve ages > 1000 years. Longevity and preservation of kauri wood in bogs made kauri a focus

<sup>&</sup>lt;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).

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