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# CURRENT PRACTICES IN BUILDING AND REPORTING AGE-DEPTH MODELS

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## ABSTRACT

Age-depth models provide essential temporal frameworks in paleoenvironmental science. We use a sample of 80 recently-published age-depth models to comment on current practices in building and reporting radiocarbon-based age models. We address options for model building, sampling strategies, dating densities, and best practices for reporting age-depth models and associated data. Our review reveals incomplete reporting of <sup>14</sup>C ages, model-building methods, age-depth models and associated meta-data in many recent studies. All information needed to evaluate, reproduce and update an age-depth model should accompany every published model. We also present a case study of building age-depth models for a lake sediment core that has both <sup>14</sup>C ages and an independent varve chronology. The case study illustrates that choosing the 'best model' is not a simple task, and that model accuracy is ultimately controlled by differences between <sup>14</sup>C ages and true age that likely occur in many late Quaternary records.

**Keywords:** age-depth modelling, chronology, accumulation rates, radiocarbon dating, varves

## INTRODUCTION

Age-depth models provide the critical temporal foundation for individual paleoenvironmental archives, and are essential for quantifying rates of change, making comparisons among proxy records, and hypothesizing drivers of environmental change. In this contribution to the *QR*

*Forum*, we use a sample of recently-published age-depth models to comment on current practices in building and reporting radiocarbon-based age models. We address options for model building, sampling strategies, dating densities, and how best to report age models and associated data. To supplement the literature sample, we also present a case study of building age-depth models for a lake sediment core that has 22 AMS  $^{14}\text{C}$  ages as well as an independent varve chronology, which we use to assess model accuracy. We do not provide an exhaustive review of current practices, nor a comprehensive guide to building age-depth models. Instead, our intention is to cast light and prompt discussion on the building and reporting of  $^{14}\text{C}$ -based age models.

To take stock of current practices, we examined all papers published in 2018 and 2019 in *Quaternary Research* and *Journal of Quaternary Science*, and identified those that included  $^{14}\text{C}$ -based age-depth models that had not been previously-published and did not rely on wiggle-matching to independent records for chronological control. We included all age-depth models regardless of sediment type or the temporal length of the record. We chose these two journals to concentrate our assessment of current practices on recently-produced models as opposed to previously published models that are often included in review papers (e.g., *Quaternary Science Reviews*), without biasing the sample towards Holocene models (e.g., *The Holocene*) or those produced for lake sediments (e.g., *Journal of Paleolimnology*). Our compilation of models from *Quaternary Research* and *Journal of Quaternary Science* resulted in a sample of 80 age-depth models published in 62 papers (Supplementary Table 1), all with unique first authors. Almost half of the papers have a first author based in North America (45%); the other half are based in Europe (24%), China (13%) or elsewhere (18%). About half of the age models (59%) are fit to lake sediments, and the remaining are fit to peat (19%), marine sediment (13%), or other types of sediments (10%) such as loess, colluvium and floodplain deposits (Table 1). We take this to be a small but representative sample that provides sufficient grounds to comment on current practices in building and reporting  $^{14}\text{C}$ -based age-depth models. We did not observe a journal effect in any of our assessments i.e., current practices in papers published in the two journals appear to be more or less equivalent.

## **CLASSICAL AND BAYESIAN AGE-DEPTH MODELS**

In the last decade, the practice of modelling the relationship between depth and age has been advanced through wide availability of statistical code or programs for "classical" approaches

such as *clam* (Blaauw, 2010) and Bayesian modelling such as *OxCal* (Bronk Ramsey, 2008), *Bchron* (Haslett and Parnell, 2008) and *Bacon* (Blaauw and Christen, 2011). An important advantage of using one of these programs is the  $^{14}\text{C}$  age calibration process that is dynamically included in the construction of models through repeated random sampling of the calibration distributions (Telford et al., 2004a, 2004b; Michczynski, 2007; Blaauw, 2010). Regardless of the type of model chosen, consideration of full calendar age probability distributions during model construction is a more robust approach than calibrating each  $^{14}\text{C}$  age in isolation (e.g., using CALIB; Stuiver and Reimer, 1993) and then building an age model on the single calibrated age estimates (e.g., the weighted average or median of the probability distribution). While most of the models in our literature sample took advantage of the built-in age calibration in one of these programs, 20% of the models were built on  $^{14}\text{C}$  ages that were reduced to single calibrated age points before model building. In some cases, these models might be reasonable approximations of the true age-depth relationship, but given that code and programs with built-in calibration processes are now readily available, this approach should be abandoned.

The simplest approach for constructing an age-depth model is to use linear interpolation between  $^{14}\text{C}$  ages. Linear interpolation assumes that ages are accurate and that accumulation rates between ages are linear. This was arguably the most commonly used approach for building chronologies 30 years ago (Webb and Webb, 1988). In our literature sample, 21% of recently-published age models relied on simple linear interpolation, and many of these models were built in unspecified programs (Table 1). Linear interpolation models suffer from the problem that inferred changes in accumulation rate occur only, but exactly, at every dated depth (Bennett, 1994). This means that had  $^{14}\text{C}$  ages been obtained at different depths, changes in sedimentation rate would be located at different but equally-precise positions in the sequence. As pointed out by Bennett and Fuller (2002), "*rates of sediment accumulation do not, in nature, change at the locations chosen for radiocarbon dates.*"

In many cases, a smooth sedimentation rate is more realistic, at least in cases where sediment or peat type does not change abruptly. Thus, another approach is to use one of many classes of smooth functions: 21% of models in our literature sample used a smooth, cubic or monotonic spline, whereas only a few relied on polynomial regression (Table 1). These approaches use all of the dating information from the whole sediment sequence or core to model accumulation as a function of time. These models are now typically built in the *clam* package

(Blaauw, 2010) in R. In our literature sample, 28% of all models were built using *clam* (Table 1). Unfortunately, *clam* offers few diagnostics to help choose the best model. Nonetheless, citations of *clam* have substantially increased since it was first introduced (Yue Wang et al., 2019), with researchers using *clam* to implement various smooth functions as well as linear interpolation.

An alternative methodology for age-depth modelling is to use the Bayesian techniques available in *OxCal* (Bronk Ramsey, 2008), *Bchron* (Haslett and Parnell, 2008) and *Bacon* (Blaauw and Christen, 2011). These Bayesian approaches enforce monotonicity of ages (positive accumulation rates) and incorporate assumptions about accumulation rates (e.g., Goring et al., 2012) and/or how they vary, although in each program these are based on different depositional models with different parameters. The popularity of Bayesian techniques appears to be increasing. Yue Wang et al. (2019) document a fairly consistent increase in citations of *OxCal* (Bronk Ramsey, 2008) and *Bacon* (Blaauw and Christen, 2011), although in many cases *OxCal* is used solely for  $^{14}\text{C}$  age calibration and not model building. Half of the models in our literature sample relied on a Bayesian approach, with most of these built using *Bacon* (34%), rather than *OxCal* (14%) or *Bchron* (6%). Like *clam*, there are few diagnostic tools in these programs to help choose the best model. With *Bacon*, it is also difficult to know when to change default values for accumulation rate priors and segment lengths, and the manual provides little guidance on setting model parameters. As a consequence, of the *Bacon* models in our literature sample that reported priors, most (73%) used the default values, regardless of whether the model was built for lake sediment, peat, or another type of sedimentary record.

Although Bayesian techniques use a different approach in the construction of age models, the 'best-fit' model can resemble simple linear interpolation e.g., when the mean age-depth model goes through each calibrated age range with changes in accumulation rate at dated depths. Resemblance to linear interpolation occurred in half (48%) of the *Bacon* models we examined (e.g., Yongbo Wang et al., 2019; McCulloch et al., 2019) and most if not all of the *OxCal* (e.g., Frodlová et al., 2018) and *Bchron* (e.g., Schiferl et al., 2018) models. Trachsel and Telford (2017) observed that "*although Bayesian age-depth modelling routines simulate changing accumulation rates, the mean accumulation rate (that is mostly used by scientists) is fairly constant between two dated levels, and therefore, the age-depth model is a straight line between two dated levels.*" Similarity to linear interpolation is not altogether surprising, especially for *Bacon* and *Bchron*, as they are based in part on modelling piece-wise linear accumulations. For

example, Parnell et al. (2011) explain that an important constraint in *Bchron* is that a change in sedimentation rate is assumed to occur at each dated depth, thus treating each age as accurate as is the case in linear interpolation. Consequently, in the absence of many ages, these Bayesian techniques can result in a 'best-fit' model that resembles linear interpolation, albeit with improvements in uncertainty estimation (Trachsel and Telford, 2017; Blaauw et al., 2018).

Assessing the accuracy of age models requires that the true age-depth relationship be known, which is rarely the case. Model comparisons and tests of model accuracy have generally relied on simulations e.g., using varve chronologies to produce a series of simulated  $^{14}\text{C}$  ages upon which various models are built and then compared to the known varve chronology (Telford et al., 2004a). Using this approach with three independent varve chronologies, Trachsel and Telford (2017) showed that Bayesian models built in *Bacon*, *OxCal* and *Bchron* as well as a smooth spline model from *clam* each produced a mean age model close to the true varve age; however, all models were challenged to produce reliable accumulation rates. In another simulation study, Wright et al. (2017) concluded that no single modelling package (*clam*, *OxCal*, *Bchron*, and *Bacon* and its predecessor *Bpeat*) out-performed all others. Blaauw et al. (2018) compared the accuracy of linear interpolation, smooth spline, *Bacon* and *Bchron* models to a varve chronology as well as simulated hypothetical sequences, varying the dating density to further assess model accuracy. Their simulations demonstrate that, at low dating densities (<1 date per millennium, dpm), most models fail to accurately reproduce known age-depth relationships. The accuracy of all models improved as dating density increased, but this was especially the case with *Bacon*-produced models, which were more consistently accurate in their simulations, although even these models were offset from true age at high dating densities.

A significant difference between Bayesian and classical models, especially linear interpolation, lies in the estimation of age uncertainties. In Bayesian models, age uncertainties tend to increase between chronological control points e.g., with distance from  $^{14}\text{C}$  ages (Parnell et al., 2011; Trachsel and Telford, 2017; Blaauw et al., 2018). In contrast, models built with methods such as polynomial regression and smooth splines typically have uncertainties that are relatively constant between dated levels, and uncertainties in linear interpolation models may even decrease between ages (Bennett, 1994; Trachsel and Telford, 2017; Töröcsik et al., 2018). Trachsel and Telford (2017) suggest that smooth splines in *clam* usually underestimate age uncertainties and that Bayesian approaches generally provide better error estimation, although

these can be too large in *Bchron* and too large or too small in *Bacon* and *OxCal*, depending on how modelling routines are parameterized. Similarly, Blaauw et al. (2018) argue that linear interpolation and smooth splines produce age uncertainties that are too narrow and that the wider uncertainties in *Bacon* and *Bchron* are more realistic. However, age uncertainties produced by the various programs are different types of uncertainties, making their direct comparison less meaningful. The Bayesian programs provide age uncertainties for single predicted ages for a given depth (i.e., prediction intervals), whereas *clam* returns confidence intervals that are uncertainties on the mean predicted age for a given depth (Trachsel and Telford, 2017). This is a subtle but important difference that likely helps to explain why uncertainties in *clam* are almost always lower than in the Bayesian models; predicting a single age for a given depth is inherently more uncertain than predicting its mean age.

Age uncertainties are important for assessing the synchronicity of paleoenvironmental changes among records and/or sites, and identifying the drivers of such changes. There are, however, few examples in the literature of studies that explicitly integrate age model uncertainties into paleoenvironmental reconstructions (e.g., Charman et al., 2009; Blaauw et al., 2010; Chevalier and Chase, 2015). In the vast majority of studies, researchers are interested in the 'best fit' or mean modelled age for individual depths (i.e., point estimates) and pay little attention to age model uncertainties or precision. Although 84% of the papers in our literature sample showed uncertainties on a plot of the age model, none made explicit use of the uncertainties in their paleoenvironmental reconstructions. Weller et al. (2019) was the only paper to use uncertainty estimates in a tangible way i.e., in the assignment of ages to poorly-dated tephras. Consideration of age model uncertainties will need to be incorporated into paleoenvironmental reconstructions for the advances provided by Bayesian age models to be fully realized.

## DATING DENSITIES AND SAMPLING STRATEGIES

The degree of chronological control in an age-depth model acts as an important constraint on the research questions that can be answered in any given study. One basic measure of chronological control is dating density i.e., the number of ages per time interval. Blaauw et al. (2018) note that, on average, late Quaternary sites in the Neotoma database (Williams et al., 2018) have the equivalent of one  $^{14}\text{C}$  age every 1400 yr (or 0.72 dates per millennium) and that only 14% of

sites have >2 dpm. To estimate dating densities in our sample of 80 recently-published age-depth models, we included  $^{14}\text{C}$  ages as well as other chronological control points such as known tephra and ages that had been assigned to 0 cm, typically the year of sediment core collection. Only 20% of the models in our literature sample had >2 dpm; with only one exception, these well-dated records span 6000 years or less. The mean across all 80 models was 1.4 dpm (median = 1.0 dpm). Dating densities were slightly higher in models spanning the last 15,000 years or less (mean = 1.8 dpm, median = 1.4 dpm;  $n = 52$ ). On average, this indicates an age every 600 to 700 yr, which comes close to Blaauw et al.'s (2018) recommendation of obtaining a minimum of 2 dpm. Taken at face value, this suggests a respectable amount of chronological control in recently-published models, particularly in light of the constraints imposed by research funding. The accuracy of age models should generally increase with higher dating densities (Telford et al., 2004a; Trachsel and Telford, 2017; Blaauw et al., 2018), provided the ages themselves are reasonably accurate. Of course, the maximum number of dates, given funding constraints, should be obtained. However, using the mean number of ages per millennium to assess model quality ignores what we refer to below as the 'age spacing problem'.

Many of the age-depth models in our literature sample suffer from long temporal gaps between ages e.g., gaps of >3000 yr between ages in full Holocene records, gaps of >1000 yr in records spanning 3000 yr, etc. Of the 80 models, two-thirds (64%) suffered from this 'age spacing problem', leaving these records with poor chronological control in portions of the record. Some particularly-poorly constrained sequences had two or three long gaps between ages. Others had a number of ages within a short time interval, which reduces the quality of the overall age-depth model compared to having the same number of ages spread over longer intervals. Thus, the issue is not solely whether sufficient ages are being used to build age models but also how closely spaced the ages are in time. Of course, the length of tolerable gaps will depend on the research question(s). Nonetheless, we recommend, based on common sense, that researchers avoid long temporal gaps between dated levels e.g., gaps of more than 20% of the total length of the record. We acknowledge that in some cases, especially in regions such as the Arctic, long temporal gaps may be unavoidable, if there is insufficient carbon for dating in long sections of a sediment sequence. Of course, additional ages should be obtained for sequences with substantial changes in accumulation rates and those subjected to high-resolution proxy analyses.



Building a robust age model begins with choices on what to date and where along a sequence to obtain ages. Attention must be paid to deciding how many ages to obtain and what material to date (e.g., MacDonald et al., 1991; Björck and Wohlfarth, 2001; Oswald et al., 2005; Walker et al., 2007; Grimm et al., 2009; Piotrowska et al., 2011). When the number of ages is constrained by the availability of funds, the best strategy involves several iterations of dating i.e., obtaining a first batch of ages spread along the length of the sequence, including one near or at the base, followed by second and/or third batches in which additional depths are chosen strategically so that ages are more or less evenly spread in time and changes in sediment type or accumulation are considered (PALE Steering Committee, 1993; Bennett, 1994; Piotrowska et al., 2011; Blaauw et al., 2018). Large changes in accumulation rates are usually only discovered after dating; thus, dating in batches helps to produce a better model. To assess the extent to which models in our literature sample were built with ages obtained in batches, we examined the lab reference numbers reported for each  $^{14}\text{C}$  age in every paper. Because analytical labs generally number  $^{14}\text{C}$  ages in the order in which they are produced, models built on  $^{14}\text{C}$  ages obtained in a single batch should have lab numbers that are in numerical order (e.g., the UOC ages in Table 2), while  $^{14}\text{C}$  ages with notably different lab numbers or from different labs indicate iterations of dating. For the chronologies in our literature sample that reported lab numbers (26% of papers did not report lab codes), only 21% had lab numbers that were in order, suggesting that most researchers are indeed using several iterations of dating to refine their chronologies. However, we found that two-thirds (69%) of the age models with lab numbers in numerical order had the 'age spacing problem' described above. Two or more iterations of dating should help avoid long temporal gaps between ages.

As a general rule, extrapolating an age-depth model beyond the dated range of a sediment sequence should be avoided, as it assumes that the relationship between depth and time holds for sediments lacking chronological control. Extrapolation should not be used across changes in sediment or peat type. Excessive extrapolation, which we defined as 1000 years or more beyond the oldest  $^{14}\text{C}$  age, was used in only 14% of the models we examined; however, in a few cases, the age model was extrapolated by several thousand years. In cases where basal sediments lack chronological control, we recommend that proxy data below the lowest age be plotted without a timescale.

## REPORTING AGE-DEPTH MODELS

All  $^{14}\text{C}$  ages and associated methods need to be described in adequate detail if others are to successfully reproduce an age-depth model, update the model as new calibration datasets and modelling techniques are developed, or use the data in large-scale synthesis efforts. Of course, meta-data on  $^{14}\text{C}$  ages and the steps taken to build a chronology are also necessary for assessing the quality of age models and the paleoenvironmental inferences that rely on them.

We were surprised to find that one-third (34%) of the papers we examined failed to report one or more of the following: whether the ages were based on AMS or radiometric  $^{14}\text{C}$  dating, what material was dated, the name of the lab that performed the dating, and/or the lab reference numbers for each  $^{14}\text{C}$  age. In addition, nearly one-quarter (23%) of papers did not report which  $^{14}\text{C}$  calibration dataset was used. Of the 34 papers that reported  $^{14}\text{C}$  ages on bulk sediment or peat, 74% failed to report sample thickness. Sample thickness is important information for reproducing or updating an age model, as it is the midpoints of the depth ranges that should be used in age-depth modelling. A number of papers also failed to specify important parameters used in model construction. For example, 54% of papers that used *Bacon* did not report the priors that are essential to this Bayesian technique. The upper panels of a default *Bacon* age-depth plot include the priors as well as information about model iterations; however, these panels are often omitted from publications. We suspect in most cases where the priors were not reported that default values were used, as that is by far the most common approach. Information about priors along with which version of *Bacon* should always be reported, because the default priors have changed between versions. We also encourage inclusion of  $\delta^{13}\text{C}$  values for each  $^{14}\text{C}$  age but only when measured independently through isotope-ratio mass spectrometry (IRMS). These values can potentially provide information about the material being dated and/or the environmental conditions the sample is derived from.

Assigning an age to the surface or top of the sequence is now common practice. Almost two-thirds of the papers in our literature sample used an assigned top age in their age model e.g., the year of sediment core collection for 0 cm. However, the majority of papers (86%) that assigned a top age failed to report the details of the age. In some cases, it was apparent in the plot of the model that a top age was used to constrain the chronology, but this constraint was not stated in any way in the text. In other cases, the paper stated that a top age was used in the model, but the specific age and its error were not reported. In fact, the year of sediment collection,

whether it was used in the age model or not, was not reported in 40% of papers in our literature sample. When a top age is used as a control point in an age-depth model, its depth and assigned age and error must be reported.

Given the central role of age models, both a table of  $^{14}\text{C}$  ages and a plot of the model should be included. Plots of age-depth models should include both the 'best-fit' model used for proxy data as well as age uncertainty estimates. Building an age-depth model is a statistical exercise (i.e.,  $\text{age} = f(\text{depth}) + \text{error}$ ) and as such, depth belongs on the  $x$ -axis, as it is the known variable from which age is predicted (Bennett, 1994). However, in our sample of recently-published models, most placed depth on the  $y$ -axis, which implies, according to statistical convention, that depth was predicted from age.

Rejection of  $^{14}\text{C}$  ages was surprisingly common in the papers we examined. In 33% of cases, one or more  $^{14}\text{C}$  age was rejected before model building, primarily because of age reversals. In many cases, rejected ages are not included in the plot of the age-depth model. We recommend including rejected ages not only in the table of ages but also in the age model plot, as this aids assessment of the context, validity and implications of age rejections. All of the model-building programs discussed above include some sort of 'outlier' argument or command that can be used to plot a rejected age while still excluding it from the model.

## **LAC NOIR: A CASE STUDY IN AGE-DEPTH MODELLING**

Simulation studies such as those by Trachsel and Telford (2017) and Blaauw et al. (2018) provide much-needed insight into the performance of age-depth models. However, as pointed out by Telford et al. (2004a), these simulations are often conducted under conditions that are notably different from building age models with real datasets: the simulated ages are accurate, precise and often equally-spaced, and there are no concerns about contamination, reservoir effects, hiatuses, or extreme changes in accumulation rates.

Here, we compare a series of age-depth models built for a well-dated lake sediment core that has an independent varve chronology. This provides an opportunity to assess the performance and accuracy of models built on real ages, as opposed to simulations. The sediment core is from Lac Noir (45°46.53'N, 75°8.10'W) in southwestern Québec, Canada (Neil and Gajewski, 2018), is 5.43 m long, and has 22 AMS  $^{14}\text{C}$  ages (Table 2), resulting in a dating density of 2 dpm. The sediments are continuously laminated to a depth of 5.24 m with varves

spanning the last 11,160 cal yr. We treated the varve chronology as true and accurate, although replicate varve counts indicate counting imprecision of 1.5 to 6.7% depending on the core section (Neil and Gajewski, 2018). We fit the three most common types of models encountered in our literature sample: a Bayesian model using the default priors in *Bacon* (vers. 2.3.9.1), and linear interpolation and smooth spline models using *clam* (vers. 2.3.2). We also fit a 2<sup>nd</sup>-order polynomial, as it represents an end-member of models to choose from and polynomials were commonly used in older studies. For linear interpolation, we excluded the <sup>14</sup>C age at 280 cm (Table 2) prior to model construction. The age is from a 'flat' portion of the calibration curve and causes a minor age reversal. Thus, excluding this age was necessary for linear interpolation but unnecessary when fitting the other models. In a second iteration, we built all four models using only every second <sup>14</sup>C age to assess their performance at a dating density (i.e., 1 dpm) that is typical of many published studies. In all cases, we used an age of  $-62 \pm 2$  cal yr BP for 0 cm, based on the year of core collection (2012). We focus on the 'best-fit' models (Figs. 1 and 2) and their associated sediment accumulation rates (Fig. 3), as these have important implications for estimating proxy accumulation rates, and place less emphasis on estimated age uncertainties as these are not directly comparable between *Bacon* and *clam*.

The mean age-depth model from *Bacon* goes through each calibrated age range with age uncertainties that are mostly between 275 and 500 yr (Figs. 1A and 2A). Linear interpolation behaves similarly (Fig. 1A), but its uncertainties (not shown) are mostly smaller (150 to 350 yr). The median differences between the *Bacon* and linear interpolation models compared to the varve chronology are 223 and 228 yr, respectively (Fig. 2A). It is difficult to distinguish the 'best-fit' *Bacon* and linear interpolation models, except in the few sections of the core where they differ (Fig. 1A). However, differences are readily apparent in their estimated accumulation rates (Fig. 3B), which show the linear segments fit in each case i.e., between pairs of <sup>14</sup>C ages in linear interpolation and for each of the 5-cm segments in *Bacon*. The mean model from *Bacon* introduces high frequency changes in accumulation rates that vary in amplitude, whereas for linear interpolation, rate changes are mostly high in amplitude with their frequency more tightly controlled by the position of the <sup>14</sup>C ages. At the lower dating density, the two models (Fig. 2B) and their accumulation rates (Fig. 3C) are almost indistinguishable, although *Bacon* retains high frequency changes in rates linked to segment length. This underscores the importance of high dating densities when fitting models in *Bacon* (Blauw et al., 2018). At the lower dating density,

the Lac Noir accumulation rates of the mean model from *Bacon* are not substantially different from simple linear interpolation.

The smooth spline (Figs. 1B and 2A) fit in *clam* also goes through each calibrated age range, but its age uncertainties are generally smaller than the *Bacon* model. Uncertainties are generally between 130 and 260 yr but are up to 600 yr in the late Holocene where *Bacon* also returns large uncertainties. The median difference between the smooth spline and the varve chronology is 231 yr, which is similar to *Bacon* and linear interpolation, and down-core changes in accuracy are also similar to *Bacon* (Fig. 2A). Accumulation rates for the smooth spline generally increase and decrease in concert with those of *Bacon* (Fig. 3B), although rate changes are sometimes higher or lower in amplitude. At the lower dating density, changes in accumulation rates for the smooth spline are, of course, smoother but are also generally similar to *Bacon* and linear interpolation over the long-term (Fig. 3C).

As expected, the 2<sup>nd</sup>-order polynomial produces an even smoother age-depth model (Fig. 1B), uncertainties are at their lowest and have a relatively constant width (~100 yr for most depths), and accumulation rates are also relatively constant for much of the sediment core (Fig. 3A). The median difference compared to the varve chronology is 129 yr, which is substantially lower than the other three models (Fig. 2A). At the lower dating density, the polynomial model and its accumulation rates are essentially unchanged, although this is not surprising for a low-degree polynomial.

Comparison to the Lac Noir varve chronology shows that all models are accurate in some sections but over- or underestimate age in others (Figs. 1 and 2). In addition, linear interpolation, *Bacon* and the smooth spline over-estimate variability in accumulation rates compared to those based on varve thickness, and changes are frequently out of phase (Fig. 3B). Although most of the calibrated age ranges at Lac Noir overlap the varve chronology (Fig. 1), <sup>14</sup>C ages between 450 and 360 cm depth (~8400 and 6000 cal yr BP) are generally younger than the corresponding varve age and those above 220 cm depth (<3000 cal yr BP) are generally older. These systematic offsets may be related to changes in plant communities, lake chemistry and/or other environmental conditions. Regardless, these age offsets highlight another important consideration in the construction of age-depth models: each <sup>14</sup>C age is merely a sample of  $n=1$  of the total population of ages for any given depth. Thus, it should not be surprising when <sup>14</sup>C ages, and models based on them, deviate from true age. In the case of Lac Noir, none of the modelled

age uncertainties fully encapsulate the varve chronology. The default *Bacon* model is most successful in this regard, but even in this case, the age uncertainties encompass the varve chronology for only 40% of the record's length (Figs. 1A and 2A).

Given that all of the models over and under-estimate age in similar sections of the record, there is no obvious choice for the 'best model'. In general, the smooth spline and polynomial are more effective at mimicking the smoothness of the varve chronology over the long term. If proxies such as loss-on-ignition or magnetic susceptibility are also smooth (as at Lac Noir; Neil and Gajewski, 2018), then a smooth model may be a reasonable choice. Among all four models, the polynomial has the lowest deviations, on average, from the varve chronology (Fig. 2A), but it clearly underestimates variability in accumulation rates, especially in the past ~4000 years (Fig. 3A). The 'best-fit' *Bacon* model is an improvement over simple linear interpolation and is fairly similar to the smooth spline (Fig. 2A), although *Bacon* appears to overestimate variability in accumulation rates (Fig. 3B), as also shown by Trachsel and Telford (2017). Increasing the segment length in *Bacon* from the default 5 cm to match the median (20 cm) or mean (25 cm) distance between  $^{14}\text{C}$  ages further increases the resemblance between *Bacon* and linear interpolation, although changes in the *Bacon*-produced accumulation rates sometimes lead or lag the position of the  $^{14}\text{C}$  ages. Wright et al. (2017) found similar phase offsets with *Bacon*-produced models.

Interestingly, the modelled ages and accumulation rates of all four models are as or more similar to the varve chronology when fit using only half of the 22  $^{14}\text{C}$  ages (Figs. 2B and 3C). At the lower dating density (Fig. 2B), the median difference compared to the varve chronology is lowest for the polynomial (110 yr) and highest for the *Bacon* model (200 yr). For Lac Noir, a higher dating density does not result in a more accurate age model (cf. Blaauw et al., 2018). The overall pattern of sediment accumulation at Lac Noir is smooth and broadly linear, and fewer dates result in less scatter, so it is not surprising that models built using a lower dating density have similar or better accuracy. However, this is not likely to be the case for records with more substantial changes in sedimentation rates. Simulation studies have shown that low dating densities typically decrease model accuracy (Telford et al., 2004a; Trachsel and Telford, 2017; Blaauw et al., 2018).

In light of our model comparisons using the Lac Noir record as well as the simulation studies of others (Telford et al., 2004a; Trachsel and Telford, 2017; Wright et al., 2017), we

cannot support the blanket recommendation by Blaauw et al. (2018) that Bayesian models be used in building chronologies, to the apparent exclusion of other types of models. Much depends on dating densities, age scatter, outliers, and down-core changes in sediment type and accumulation rates. Instead, as suggested by Blockley et al. (2007), an array of models could be entertained along with assessment of how well each approximates the chronological data and satisfies other information such as changes in sediment type or other properties. This approach should clarify what effects, if any, the routines and assumptions of each modelling approach have on the resulting age model and accumulation rates, and may suggest, at least informally, the confidence that can be attached to conclusions based on associated proxy data. In addition, modelled accumulation rates should not be blindly imposed on proxy data e.g., in calculating pollen or carbon accumulation rates. Attention should be paid to how model-driven changes in accumulation rates might affect paleoenvironmental inferences from proxy accumulation rates. To be clear, we are not suggesting that researchers fit all possible models and choose the one deemed most desirable. Rather, we are arguing against the other extreme of relying solely on a single modelling technique for all scenarios. Consideration should be given to whether the chosen model, Bayesian or not, is sensible given other evidence on the age-depth relationship and the history of sediment or peat accumulation.

## **LOOKING FORWARD**

Our recommendations on best practices for building and reporting age-depth models are not new nor are they exhaustive, but they bear repeating. When building an age-depth model,  $^{14}\text{C}$  ages should not be reduced to single calibrated age estimates before model construction, as there are now a number of modelling options with built-in age calibration. To the extent possible, researchers should avoid long temporal gaps between ages. Obtaining  $^{14}\text{C}$  ages in batches is part of an effective strategy for avoiding long temporal gaps. High density dating is particularly important for sequences with substantial changes in accumulation rates and those subjected to high-resolution proxy analyses. Extrapolation beyond chronological control points is rarely justified. Our review of recent studies illustrates that better reporting of  $^{14}\text{C}$  ages, model-building methods, age-depth models and associated meta-data is needed. All information needed to evaluate, reproduce and update an age model should accompany every published model. This includes reporting the material that was dated, sample thicknesses, radiocarbon lab names and

reference codes, and calibration datasets. Details on assigned surface ages, rejected ages and all modelling parameters including Bayesian priors should also be reported.

Varve chronologies such as Lac Noir and others used in simulation studies (Telford et al., 2004a; Trachsel and Telford, 2017; Blaauw et al., 2018) are useful in assessing model accuracy, but sedimentation in varved records tends to be fairly smooth and broadly linear. In contrast, two-thirds of the age-depth models in our literature sample had sigmoidal, concave or convex shapes. Future assessments of model performance should attempt to address these more complicated but routinely-encountered age-depth relationships. In addition, user-friendly code for comparing models produced by different programs and more diagnostic tools for choosing the 'best model' would help advance efforts to identify robust age models. More work is needed to determine best practices for incorporating age model uncertainties into paleoenvironmental reconstructions. It would be helpful if an option for prediction intervals were added to *clam*, where this is feasible (e.g., splines, polynomials), as it is the most widely used program for classical age-depth modelling. This would facilitate comparison of model uncertainties among classical and Bayesian techniques, as the uncertainties that are currently provided are not directly comparable in a statistical sense. Approaches for integrating depth uncertainties (e.g., sample thicknesses) into age-depth models and for combining  $^{14}\text{C}$  and  $^{210}\text{Pb}$  ages in a single age model also warrant further investigation.

The case study at Lac Noir highlights the offsets between  $^{14}\text{C}$  ages and true age that may very well occur in many late Quaternary records. Obtaining high-precision AMS  $^{14}\text{C}$  ages on tiny discrete samples, in lieu of low-precision radiometric ages on bulk sediments, is now common practice. It is difficult to know if this approach might be increasing the likelihood that any given  $^{14}\text{C}$  age is offset from true age (Oswald et al., 2005; Walker et al., 2007). Regardless, these potential offsets are important to bear in mind. Age-depth model accuracy is ultimately controlled by the accuracy of the ages themselves.

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**TABLE 1:** Summary of 80 radiocarbon-based age-depth models published in *Quaternary Research* and *Journal of Quaternary Science* in 2018 and 2019.

Type of Deposit (n)	Type of Model (n)	Model software (n)
Lake sediment (47)	Bayesian (44)	<i>Bacon</i> (27)
Peat (15)	Linear interpolation (17)	<i>clam</i> (22)
Marine sediment (10)	Spline (17)	Not specified (13)
Loess (2)	Polynomial regression (2)	<i>OxCal</i> (11)
Other (6)		<i>Bchron</i> (5)
		Other (2)

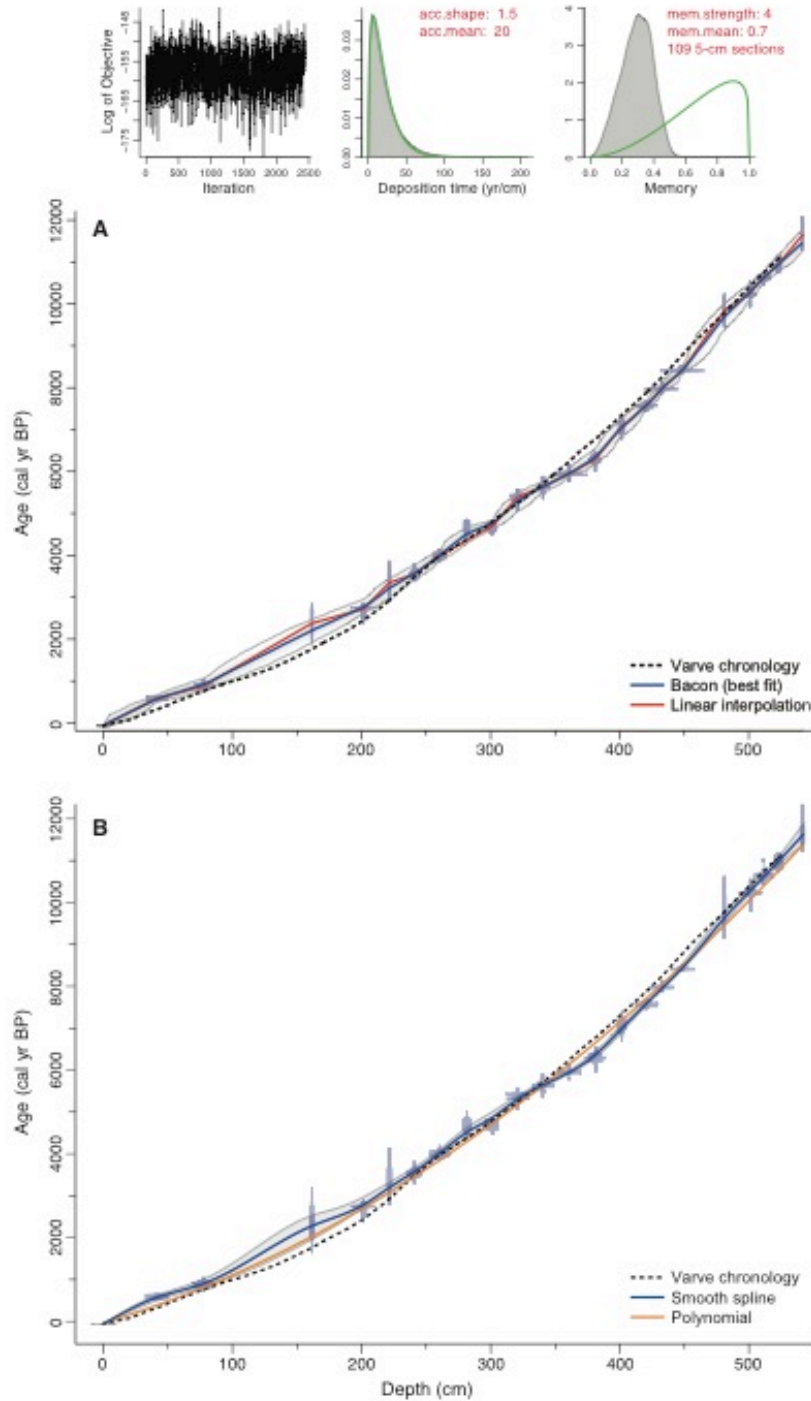
**TABLE 2:** AMS radiocarbon ages from Lac Noir, southwestern Québec, Canada from Neil and Gajewski (2018). All  $^{14}\text{C}$  ages are on plant remains including leaf fragments, seeds and needles.

<b>Depth (cm)</b>	<b>Radiocarbon age (<math>^{14}\text{C}</math> yr BP <math>\pm 1\sigma</math>)</b>	<b>Calendar Age <sup>a</sup> (cal yr BP)</b>	<b>Lab Number <sup>b</sup></b>
41–42	580 $\pm$ 40	530–650	Beta-276987
77–78	980 $\pm$ 40	800–960	Beta-276988
160–163	2346 $\pm$ 168	1990–2760	UOC-5286
200–203	2599 $\pm$ 43	2500–2790	UOC-5287
220–223	3201 $\pm$ 141	3060–3820	UOC-5288
240–242	3310 $\pm$ 51	3410–3680	UOC-5289
260–261	3660 $\pm$ 30	3900–4080	UOC-5290
280–283	4159 $\pm$ 64 <sup>c</sup>	4530–4840	UOC-5291
300–302	4134 $\pm$ 26	4550–4820	UOC-5292
320–322	4639 $\pm$ 38	5300–5470	UOC-5293
340–341	4894 $\pm$ 58	5480–5840	UOC-5294
360–361	5183 $\pm$ 25	5910–5990	UOC-5295
380–382	5492 $\pm$ 63	6130–6410	UOC-5296
400–403	6170 $\pm$ 71	6900–7250	UOC-5297
420–421	6708 $\pm$ 43	7500–7660	UOC-5298
432–433	7149 $\pm$ 27	7940–8010	UOC-5299
448–449	7621 $\pm$ 27	8380–8450	UOC-5300
480–482	8769 $\pm$ 155	9530–10,210	UOC-5301
500–502	9078 $\pm$ 65	9960–10,480	UOC-5302
511–512	9404 $\pm$ 33	10,560–10,730	UOC-5303
522–524	9610 $\pm$ 35	10,780–11,160	UOC-5304
540–543	10,080 $\pm$ 82	11,310–11,990	UOC-5305

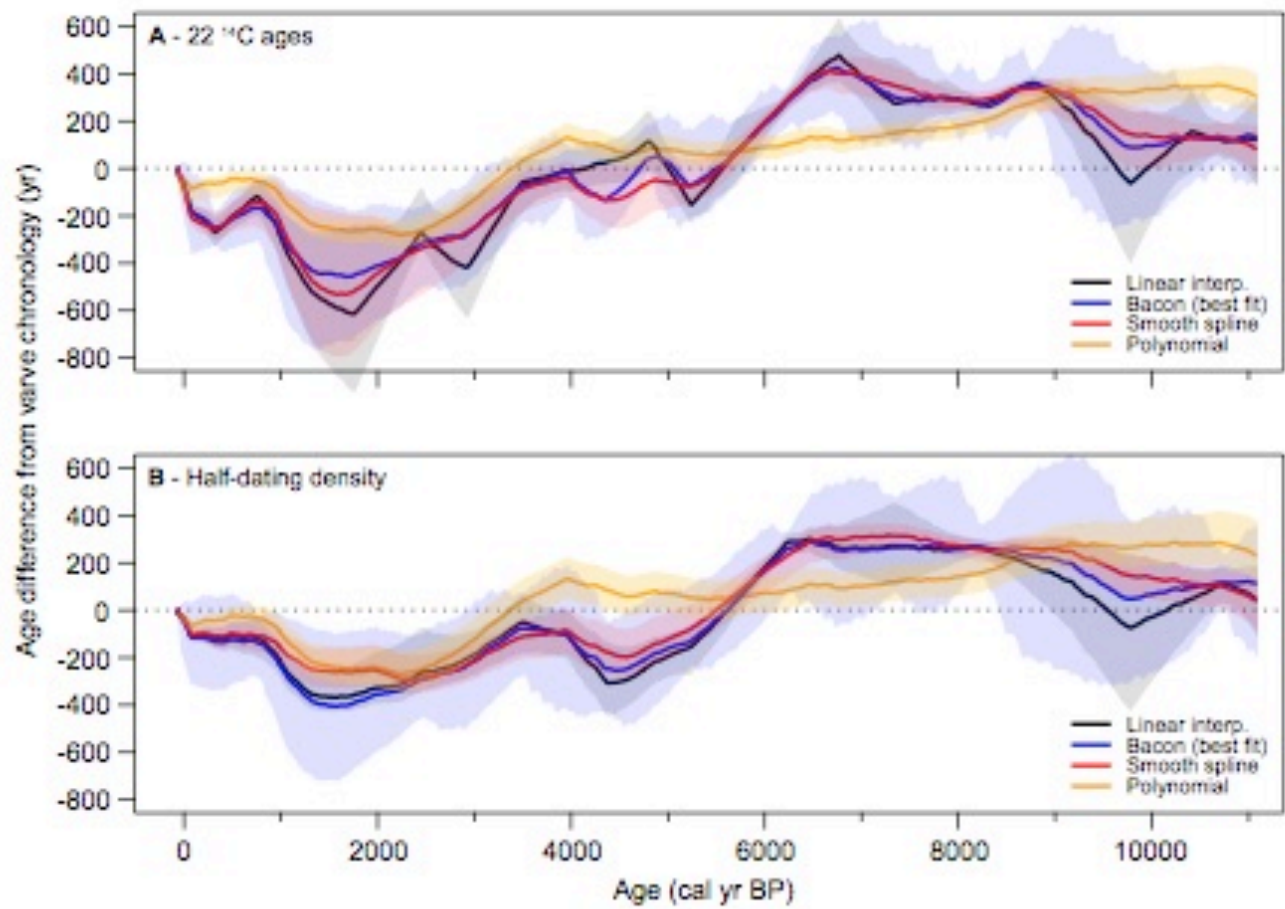
<sup>a</sup>  $2\sigma$  calendar age range rounded to the nearest 10 yr; from CALIB 7.1 based on IntCal13 (Reimer et al., 2013)

<sup>b</sup> Beta = Beta Analytic Inc.; UOC = University of Ottawa A.E. Lalonde AMS Laboratory

<sup>c</sup> Excluded from the linear interpolation models in Figs. 1A, 2A, and 3B

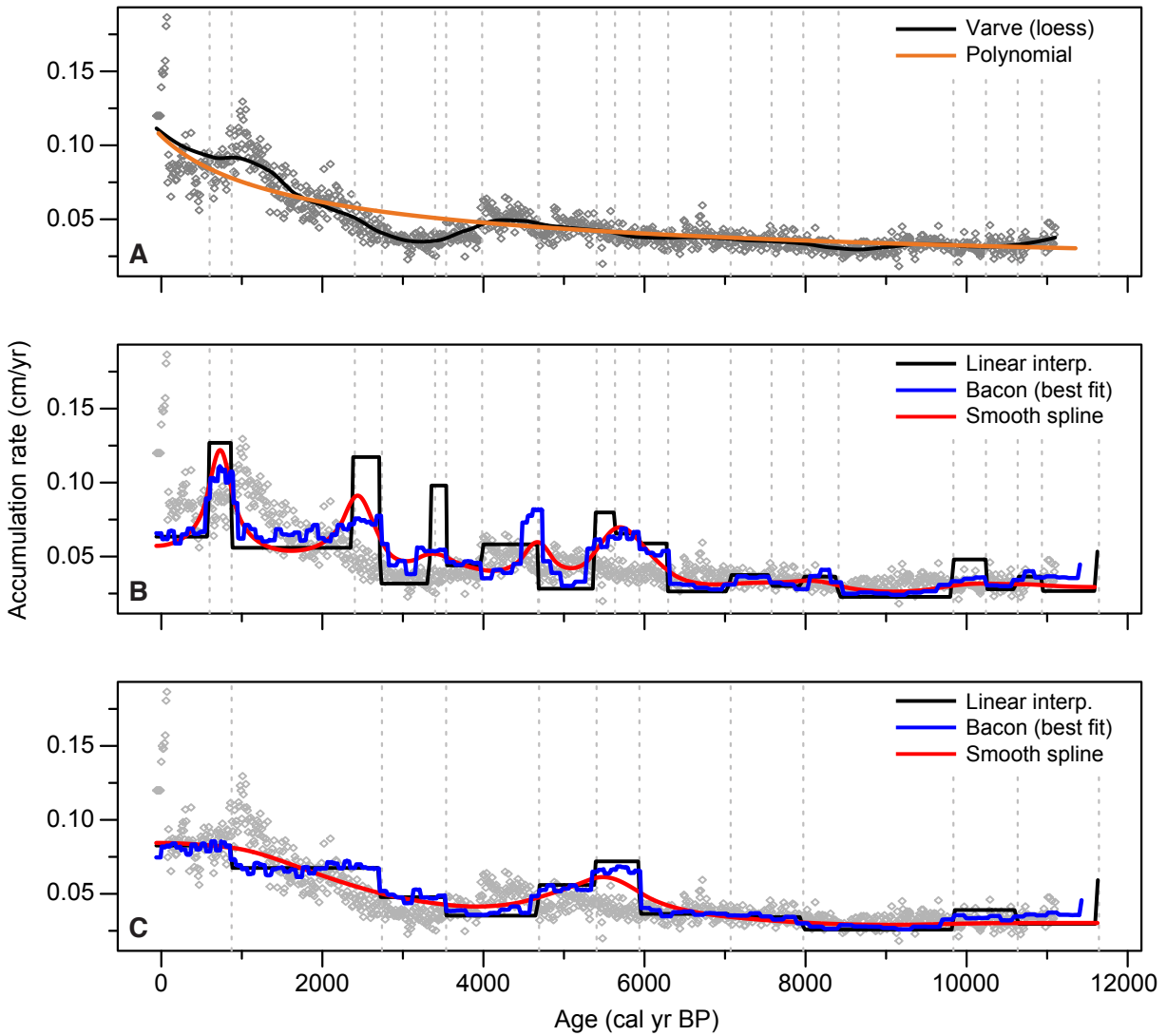


**FIGURE 1:** Age-depth models fit to the AMS radiocarbon ages from Lac Noir (Table 2) and an age of  $-62 \pm 2$  cal yr BP for 0 cm. Blue symbols show the 22 calibrated  $^{14}\text{C}$  ages and their probability distributions as calibrated by *Bacon* vers. 2.3.9.1 and *clam* vers. 2.3.2. All *clam* models were run with 10,000 iterations. **(A)** Mean age-depth model from *Bacon* (blue) built using default priors of 20 yr  $\text{cm}^{-1}$  and 1.5 for mean deposition time and shape, respectively, with its 95% prediction intervals in grey. Linear interpolation model (red) from *clam* without confidence intervals and the varve chronology (dashed black) are also shown. Prior to model construction, the  $^{14}\text{C}$  age at 280 cm was excluded from the linear interpolation model only. The linear interpolation model (red) is mostly obscured by the 'best-fit' *Bacon* model (blue) because of their similarity. **(B)** Smooth spline model (blue) and its 95% confidence intervals in grey, built with default smoothing of 0.3 in *clam*. A 2<sup>nd</sup>-order polynomial model (orange) from *clam* without confidence intervals and the varve chronology (dashed black) are also shown.



**FIGURE 2:** Difference in years between the Lac Noir varve chronology and each age-depth model in Figure 1 and their uncertainties, when built using (A) all 22 <sup>14</sup>C ages and (B) only every second <sup>14</sup>C age in Table 2.





**FIGURE 3:** Accumulation rates for the age-depth models in Figure 1. In all panels, rates based on varve thickness measurements are shown as open grey symbols and vertical dashed lines show the median of the probability distribution of each calibrated  $^{14}\text{C}$  age. **(A)** Loess curve (black; loess span=0.2) fit to accumulation rates based on varve thickness, and accumulation rates from the 2<sup>nd</sup>-order polynomial model (orange) in Fig. 1B. **(B)** Accumulation rates based on the default 'best-fit' Bacon model (blue) in Fig. 1A showing its 5-cm linear segments, linear interpolation (black) in Fig. 1A, and the clam-based smooth spline (red) with default smoothing of 0.3 in Fig. 1B. **(C)** The same as panel B, except models are based on only every second  $^{14}\text{C}$  age in Table 2 to mimic a more typical dating density.

## SUPPLEMENTARY MATERIAL

**Supplementary Table 1** List of 62 papers used by Lacourse and Gajewski (2020) to assess current practices in building and reporting age-depth models. \* = paper with more than one age-depth model

Author	Year	Title	Journal	Volume, Page numbers
Alivernini et al.	2018	Ostracod-based reconstruction of Late Quaternary lake level changes within the Tangra Yumco lake system (southern Tibetan Plateau)	Journal of Quaternary Science	33, 713–720
Alt et al.	2018	Millennial scale climate-fire-vegetation interactions in a mid-elevation mixed coniferous forest, Mission Range, northwestern Montana, USA	Quaternary Research	90, 66–82
Anderson et al.	2018	Southern Hemisphere westerly wind influence on southern New Zealand hydrology during the Lateglacial and Holocene	Journal of Quaternary Science	33, 689–701
Anderson et al. *	2019	Postglacial vegetation community change over an elevational gradient on the western Kenai Peninsula, Alaska: pollen records from Sunken Island and Choquette Lakes	Journal of Quaternary Science	34, 309–322
Andrews et al. *	2018	Sea ice, ice-rafting, and ocean climate across Denmark Strait during rapid deglaciation (~16–12 cal ka BP) of the Iceland and East Greenland shelves	Journal of Quaternary Science	33, 112–130
Behling and Oliveira	2018	Evidence of a late glacial warming event and early Holocene cooling in the southern Brazilian coastal highlands	Quaternary Research	89, 90–102
Behrens et al.	2019	Meltwater discharge during the Holocene from the Wilkes subglacial basin revealed by beryllium isotope analysis of marine sediments	Journal of Quaternary Science	34, 603–608
Benes et al.	2019	Postglacial vegetation dynamics at high elevation from Fairy Lake in the northern Greater Yellowstone Ecosystem, Montana, USA	Quaternary Research	92, 365–380
Benson et al. *	2019	A 16,000-yr-long sedimentary sequence from Lakes Peters and Schrader (Nerukpuk Lakes), northeastern Brooks Range, Alaska	Quaternary Research	92, 609–625
Berg et al.	2019	Holocene glacier fluctuations and environmental changes in subantarctic South Georgia inferred from a sediment record from a coastal inlet	Quaternary Research	91, 132–148
Bobek et al.	2018	Biotic controls on Holocene fire frequency in a temperate mountain forest, Czech Republic	Journal of Quaternary Science	33, 892–904
Brown et al.	2018	Lateglacial/early Holocene palaeoenvironments in the southern North Sea Basin: new data from the Dudgeon offshore wind farm	Journal of Quaternary Science	33, 597–610
Cadd et al.	2019	The influence of fine-scale topography on the impacts of Holocene fire in a Tasmanian montane landscape	Journal of Quaternary Science	34, 491–498

Author	Year	Title	Journal	Volume, Page numbers
Constantine et al.	2019	Mid- to late Holocene cooling events in the Korean Peninsula and their possible impact on ancient societies	Quaternary Research	92, 98–108
Cordova and Johnson	2019	An 18 ka to present pollen- and phytolith-based vegetation reconstruction from Hall's Cave, south-central Texas, USA	Quaternary Research	92, 497–518
Egan et al.	2019	Diatom-inferred aquatic impacts of the mid-Holocene eruption of Mount Mazama, Oregon, USA	Quaternary Research	91, 163–178
Frodlová et al. *	2018	Effect of sample size and resolution on palaeomalacological interpretation: a case study from Holocene calcareous-fen deposits	Journal of Quaternary Science	33, 68–78
Gavin et al. *	2018	Millennial-scale decline in coho salmon abundance since the middle Holocene in a coastal Oregon watershed, USA	Quaternary Research	89, 432–445
Haberyan	2018	A >22,000 yr diatom record from the plateau of Zambia	Quaternary Research	89, 33–42
Hixon et al.	2018	Nitrogen isotope ( $\delta^{15}\text{N}$ ) patterns for amino acids in lemur bones are inconsistent with aridity driving megafaunal extinction in south-western Madagascar	Journal of Quaternary Science	33, 958–968
Ivanova et al. *	2019	Postglacial paleoceanography and paleoenvironments in the northwestern Barents Sea	Quaternary Research	92, 430–449
Ivory and Russell *	2018	Lowland forest collapse and early human impacts at the end of the African Humid Period at Lake Edward, equatorial East Africa	Quaternary Research	89, 7–20
Juříčková et al. *	2019	A glacial refugium and zoogeographic boundary in the Slovak eastern Carpathians	Quaternary Research	91, 383–398
Kelly et al.	2018	Continuous human presence without extensive reductions in forest cover over the past 2500 years in an aseasonal Amazonian rainforest	Journal of Quaternary Science	33, 369–379
Kirby et al.	2018	A late Wisconsin (32–10k cal a BP) history of pluvials, droughts and vegetation in the Pacific south-west United States (Lake Elsinore, CA)	Journal of Quaternary Science	33, 238–254
Kock et al.	2019	Late Holocene environmental changes reconstructed from stable isotope and geochemical records from a cushion-plant peatland in the Chilean Central Andes (27°S)	Journal of Quaternary Science	34, 153–164
Krause et al.	2019	Late Quaternary vegetation, climate, and fire history of the Southeast Atlantic Coastal Plain based on a 30,000-yr multi-proxy record from White Pond, South Carolina, USA	Quaternary Research	91, 861–880
Krylovich et al.	2019	Hunter-gatherers subsistence and impact on fauna in the Islands of Four Mountains, Eastern Aleutians, Alaska, over 3000 yr	Quaternary Research	91, 983–1002
Kuzmicheva et al.	2019	A 7300-yr-old environmental history of seabird, human, and volcano impacts on Carlisle Island (the Islands of Four Mountains, eastern Aleutians, Alaska)	Quaternary Research	91, 934–952

Author	Year	Title	Journal	Volume, Page numbers
Lacourse et al.	2019	Postglacial wetland succession, carbon accumulation, and forest dynamics on the east coast of Vancouver Island, British Columbia, Canada	Quaternary Research	92, 232–245
Leithold et al.	2018	Slope failures within and upstream of Lake Quinault, Washington, as uneven responses to Holocene earthquakes along the Cascadia subduction zone	Quaternary Research	89, 178–200
Liu et al.	2019	Ecology and paleoenvironmental application of testate amoebae in peatlands of the high-elevation Colombian páramo	Quaternary Research	92, 14–32
Liu et al.	2019	Late onset of the Holocene rainfall maximum in northeastern China inferred from a pollen record from the sediments of Tianchi Crater Lake	Quaternary Research	92, 133–145
Long et al.	2019	A 7600 yr vegetation and fire history from Anthony Lake, northeastern Oregon, USA, with linkages to modern synoptic climate patterns	Quaternary Research	91, 705–713
Luo et al.	2019	Environmental changes in the north-east Sunda region over the last 40 000 years	Journal of Quaternary Science	34, 245–257
McCulloch et al.	2019	Late glacial and Holocene landscape change and rapid climate and coastal impacts in the Canal Beagle, southernmost Patagonia	Journal of Quaternary Science	34, 674–684
Menke et al.	2018	Cryptotephra from Lipari Volcano in the eastern Gulf of Taranto (Italy) as a time marker for paleoclimatic studies	Quaternary Research	89, 520–532
Mueller et al. *	2019	Climate and human influence on late Holocene fire regimes in the British Virgin Islands	Quaternary Research	91, 679–690
Nash et al. *	2018	Episodic deposition of Illinois Valley Peoria silt in association with Lake Michigan Lobe fluctuations during the last glacial maximum	Quaternary Research	89, 739–755
Novenko et al.	2018	Forest history, peatland development and mid- to late Holocene environmental change in the southern taiga forest of central European Russia	Quaternary Research	89, 223–236
Nunnery et al.	2019	Lake-level variability in Salar de Coipasa, Bolivia during the past ~40,000 yr	Quaternary Research	91, 881–891
Pompeani et al.	2019	The environmental impact of a pre-Columbian city based on geochemical insights from lake sediment cores recovered near Cahokia	Quaternary Research	91, 714–728
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