Double the dates and go for Bayes — impacts of model choice, dating density and quality on chronologies

Maarten Blaauw\textsuperscript{a,*}, J. Andrés Christen\textsuperscript{b}, K. D. Bennett\textsuperscript{c,d}, Paula J. Reimer\textsuperscript{a}

\textsuperscript{a}School of Natural and Built Environment, Queen’s University Belfast, Belfast BT7 1NN, Northern Ireland, United Kingdom
\textsuperscript{b}Centro de Investigación en Matemáticas CIMAT, Guanajuato 36023, Guanajuato, Mexico
\textsuperscript{c}School of Geography & Sustainable Development, University of St Andrews, St Andrews KY16 9AL, Scotland, United Kingdom
\textsuperscript{d}Queen’s Marine Laboratory, Queen’s University Belfast, Portaferry BT22 1PF, Northern Ireland, United Kingdom

Abstract

Reliable chronologies are essential for most Quaternary studies, but little is known about how age-depth model choice, as well as dating density and quality, affect the precision and accuracy of chronologies. A meta-analysis suggests that most existing late-Quaternary studies contain fewer than one date per millennium, and provide millennial-scale precision at best. We use existing and simulated sediment cores to estimate what dating density and quality are required to obtain accurate chronologies at a desired precision. For many sites, a doubling in dating density would significantly improve chronologies and thus their value for reconstructing and interpreting past environmental changes. Commonly used classical age-depth models stop becoming more precise after a minimum dating density is reached, but the precision of Bayesian age-depth models which take advantage of chronological ordering continues to improve with more dates. Our simulations show that classical age-depth models severely underestimate uncertainty and are inaccurate at low dating densities, and perform poorly at high dating densities. On the other hand, Bayesian age-depth models provide more realistic precision estimates, including at low to average dating densities, and

*Corresponding author: maarten.blaauw@qub.ac.uk

Preprint submitted to Elsevier February 8, 2018
are much more robust against dating scatter and outliers. Indeed, Bayesian age-depth models outperform classical ones at all tested dating densities, qualities and time-scales. We recommend that chronologies should be produced using Bayesian age-depth models taking into account chronological ordering and based on a minimum of 2 dates per millennium.

Keywords: age-depth model, radiocarbon dates, chronological uncertainties, Bayesian statistics

INTRODUCTION

Whenever an additional level of a sedimentary site or core is dated, our knowledge of its chronology increases (Bennett, 1994; Bennett and Fuller, 2002). However, dating is expensive and time-consuming, and it can prove challenging to collect sufficient reliable material for dating. A single radiocarbon (\(^{14}\text{C}\)) date often costs several hundred dollars, and waiting times can amount to months, or even years if several iterations of dating are required. Moreover, radiocarbon and other scientific dates have laboratory errors, the size of which reflects measurement uncertainties as well as the nature of laboratory sample treatment. Typical relative \(^{14}\text{C}\) dating errors hover around 1% (0.5% for modern accelerator mass-spectrometry (AMS) systems), however lower sample carbon contents can result in larger errors whereas higher-precision dates can be obtained with longer counting times. Given the many ways through which \(^{14}\text{C}\) or other absolute dates can be offset from their actual age, some degree of scatter is unavoidable in sequences of dates. Repeated measurements of samples within and between laboratories sometimes show more scatter than can be accounted for by reported errors (Bronk Ramsey et al., 2004; Christen and Pérez E., 2009; Scott, 2013), perhaps owing to inhomogeneous sampling or laboratory-introduced offsets. Further, at times high-resolution \(^{14}\text{C}\) dating can reveal unexpectedly large scatter for some core sections (e.g., Lohne et al., 2013; Groot et al., 2014).
Cores within the Neotoma Palaeoecology Database (neotomadb.org), which hosts data from many palaeo-sites from across the world, indicate that most late Quaternary sites have been dated using just a few \(^{14}\text{C}\) dates (median 5 dates per core). This is equivalent to ca 1 date every 1400 years or 0.72 dates per millennium (dpm) (Figure 1). Only very few sites reach much higher dating densities of ca 10–30 dpm (e.g. Kilian et al., 1995; Gulliksen et al., 1998; Lohne et al., 2013; Mauquoy et al., 2002; Blaauw et al., 2004; Southon et al., 2012). Only 14% of the sites have >2 dpm; and only 2% have >4 dpm.

Here we investigate: (i) whether current typical dating densities are sufficient for reliable chronologies; (ii) the degree to which higher dating densities enhance the precision and accuracy of chronologies; (iii) whether certain types of age-depth models provide more realistic estimates of precision and accuracy (Telford et al., 2004; Blockley et al., 2007; Parnell et al., 2011; Trachsel and Telford, 2017); and (iv) the extent to which chronologies are affected by dating error, scatter and outliers. Our analysis of existing dated cores enables estimates of chronological precision, but not accuracy because the ‘true’ sedimentation histories of the sites are unknown. Therefore we also use an existing varved record with known ages for each depth (Zolitschka et al., 2000; Trachsel and Telford, 2017) and moreover simulate hypothetical cores where the age is known for each depth. To test the chronological impact of dating quality for the simulated records, we simulate a range of values for dating error and scatter, as well as outlying dates.

**METHODS**

We used a three-step process to investigate cores dated at low to high resolutions (Figure 2). First, either existing dated cores were analysed, or accumulation histories were simulated to obtain known ages for each core depth \(sim_{acc}\). Then we either used existing radiocarbon-dated core depths or simulated their (sequential) dating \(sim_{dat}\). Finally we applied a variety of
age-depth models and analysed their precision estimates (95% confidence intervals; \( \text{sim}_{\text{age}} \)), and for cores where the accumulation history was known, we also calculated for each depth the difference between the modelled age and the known age.

**Data**

Age-depth models were produced for three datasets:

1. Cores from the Neotoma Palaeoecology Database (neotomadb.org). We analysed the dating density of all pollen cores with at least two \(^{14}\text{C} \) dates and spanning at least 500 yr, and calculated the precision of a range of age-depth models applied to these cores (Figure 1).

2. The sequence at Kråkenes (western Norway, 61.48°N, 5.7°E: Gulliksen et al., 1998; Lohne et al., 2013), which has 118 AMS \(^{14}\text{C} \) ages over the interval ca 14–8 kcal BP (thousands of years before AD 1950) (so ca. 20 dpm). In order to estimate the effect of increasing dating density, we removed all but the topmost and bottommost dates, and then sequentially added actual single dates (using the method outlined below) until we reached 20 dpm (Figure 3). At each step, the precision of a range of age-depth models was calculated.

3. A record from Lake Holzmaar (western Germany, 50.12°N, 6.9°E: Zolitschka et al., 2000; Telford et al., 2004; Trachsel and Telford, 2017). We took the varve-counted age-depth model as ‘true’ accumulation history, and used this to simulate radiocarbon ages (see later) and to analyse the precision as well as the accuracy of a range of age-depth models (Figures 4, 5).

*Simulated sequences (\( \text{sim}_{\text{acc}} \))*

Besides using real-world data sets, we also simulated hypothetical cores (Figure 4). Sedimentation was simulated by modelling the deposition time
represented within each depth section \( ds_i \), defined as the time span between depth \( d_i \) and the next depth \( d_{i+1} \) of a core (default every cm between 0 and 500 cm). Unless stated otherwise, the deposition time at the topmost section was sampled from a gamma distribution as in Blaauw and Christen (2011) with \( acc_1 \sim \text{Gamma}(acc.shape, acc.shape/acc.mean) \), defaults 50 yr cm\(^{-1}\) and 1.1 for mean and shape, respectively. Its top age, \( \theta_0 \), was set as 0 cal BP, unless stated otherwise. The deposition rate of each section \( ds_i \) was modelled to deviate from the preceding section \( ds_{i-1} \) by a random value sampled from a uniform distribution with width \( 2 \times acc.var \) (default 3.0), where deposition times could not go below \( acc.min \) (default 5.0 yr cm\(^{-1}\));

\( acc_i \sim \max(acc.min, acc_{i-1} + \text{Unif}(-acc.var, acc.var)) \). These simulated deposition histories then provided the ‘true’ calendar age for each depth of the simulated cores, \( \theta(d_i) \).

The \( \text{sim}_{acc} \) simulations presented here aim to model what we consider to be realistic accumulation histories of commonly studied sites such as Holocene lakes or bogs. To our knowledge, sedimentation processes have hardly been investigated. Bennett and Buck (2016) study how basin shapes could affect long-term sedimentation patterns, and Goring et al. (2012) investigated the accumulation histories of a large number of sites to identify common patterns. Bayesian age-depth modelling approaches that take into account chronological ordering, such as OxCal’s \( P_{\text{sequence}} \) (Bronk Ramsey, 2008), \( \text{Bchron} \) (Haslett and Parnell, 2008) and \( \text{Bacon} \) (Blaauw and Christen, 2011) model sedimentation by sampling from Poisson, gamma, and gamma+beta distributions respectively. The modelled variability of our \( \text{sim}_{acc} \) simulations also looks similar to that of the varved Holzmaar record (Figure 2), with long stretches of relatively constant sedimentation followed by relatively abrupt shifts. As an alternative to the section-wise random simulation of sedimentation, we also simulated a core by drawing a smooth spline through the “Example” core of \( \text{clam} \) (Blaauw, 2010). We did not invoke more chronologically disruptive features such as hiatuses, slumps, extremely variable
accumulation rates, large sections without datable material, or systematic $^{14}$C age offsets, but these could be investigated.

**Dating**

We either used existing dates (Neotoma, Kråkenes) or simulated dates ($sim$$_{dat}$; Holzmaar, simulated cores). Radiocarbon dates were used, but other types of dates could also be investigated. For Holzmaar and the simulated sequences, the ‘true’ calendar age for each depth $\theta(d_i)$ was known and was used to simulate $^{14}$C dates. Uncertainty in having sampled material contemporaneous to the depth was then simulated by adding random variation $x_{scat}$ (default 10 yr) from a normal distribution $\theta' \sim N(\theta, x_{scat}^2)$.

Additionally, with a probability $p_{out}$ (default 5%), the dates were modelled to be outlying and shifted by up to $x_{shift}$ (default 1000) years:

$$\theta'' = \begin{cases} 
\text{Unif}(\theta' - x_{shift}, \theta' + x_{shift}) & p_{out} \\
\theta' & 1 - p_{out}
\end{cases}$$

(1)

Then we used the IntCal13 $^{14}$C calibration curve (Reimer et al., 2013), which provides estimates of the $^{14}$C age $\mu(\theta)$ for each calendar age $\theta$. We simulated a $^{14}$C date by taking the IntCal13 $^{14}$C age of $\theta''$, $\mu(\theta'')$, and adding some scatter $y(\theta'') \sim N(\mu(\theta''), \sigma^2)$ where the laboratory error $\sigma = \max(\sigma_{min}, y_{scat} \times \epsilon \times \mu(\theta''))$, with $\sigma_{min}$ the minimum error (default 20 $^{14}$C yr), $y_{scat}$ an error multiplier (default 1.5) and $\epsilon$ the analytical uncertainty (default 1%).

**Sequential dating ($sim$$_{dat}$)**

For Kråkenes, Holzmaar and the simulated cores, after each age-depth model $sim$_$age$ was run (see below), we used that age-depth model to determine which depth to date next (Figure 4). Dating strategies were investigated by Buck and Christen (1998) and Christen and Buck (1998) using simulations that
were computationally extremely time-consuming. Here we adopt a much faster sampling design score developed by Christen and Sansó (2011). This simple version of the sequential Active Learning Cohn strategy as used in robotics, predicts which next data point among all available candidates is likely to provide the most new information. Only one candidate depth is selected at a time. Given that it generally takes weeks to months to obtain one date, this is not a realistic scenario for real-life $^{14}$C dating, so, in future work, we plan to enable dating in batches.

Let $s_1, s_2, \ldots, s_M$ be the depths at which we may take a sample to be dated (by radiocarbon or otherwise). Let $d_1, d_2, \ldots, d_m$ (a subset of the $s_i$) be the depths at which we already have dates $y_m = (y_1 \pm \sigma_1, y_2 \pm \sigma_2, \ldots, y_m \pm \sigma_m)$. Let $\text{cov}(d_i, d_j)$ be the covariance of depths $d_i$ and $d_j$ calculated from the joint posterior distribution of the age-depth model using the currently dated depths, that is $G(d|y_m)$. This covariance structure may be approximated using the Monte Carlo output to estimate the chronology (see below) (Haslett and Parnell, 2008; Blaauw, 2010; Blaauw and Christen, 2011). For all iterations $t = 1, 2, \ldots, T$, we calculate the covariance of the corresponding ages $G(s_i|\theta(t), \mathbf{x}(t))$ and $G(s_j|\theta(t), \mathbf{x}(t))$. Let also $V(s_i) = \text{cov}(s_i, s_i)$ be the variance at depth $s_i$. The score $A$ for a new candidate depth $d_{m+1}$ to be dated is (Christen and Sansó, 2011):

$$A(d_{m+1}) = (1 - ||r(d_{m+1})||) \frac{1}{M} \sum_{j=1}^{M} \frac{\text{cov}(s_j, d_{m+1})^2}{V(s_j)V(d_{m+1})},$$

where

$$||r(d_{m+1})|| = \sqrt{\sum_{k=1}^{m} \frac{\text{cov}(d_k, d_{m+1})^2}{V(d_k)V(d_{m+1})}}.$$

The score has a formal justification in terms of maximizing the reduction in predictive variance of the new sample point $d_{m+1}$. Intuitively, the score
chooses a new sample point that is correlated with other locations given the term
\[ \frac{1}{M} \sum_{j=1}^{M} \frac{\text{cov}(s_j, d_{m+1})^2}{V(s_j)V(d_{m+1})}, \]
and consequently favours depths with higher variance in their age estimates (large uncertainties), as well as depths which provide more information about the ages of other depths in the sequence (high covariance). However, the term \(1 - \|r(d_{m+1})\|\) penalizes depths correlated with locations already sampled, thus separating the dated depths (see Christen and Sansó, 2011, for further intuitive and technical justifications of the score and some examples showing its performance).

The approach presented here can be applied to individual core sections as well as to whole sequences. We note that it often makes scientific and financial sense to only apply higher dating resolutions, and thus reach higher chronological precision, for specific core sections of interest (e.g. the 1-m long sections discussed further below).

**Age-depth modelling \(\text{sim}_{\text{age}}\)**

We applied four types of age-depth models, which produced thousands to millions of iterations to provide distributions of calendar age estimates for each core depth. We first used the popular classical model of linear interpolation as implemented in \textit{psimpoll} (Bennett, 2007) and \textit{clam} (Blaauw, 2010), which assumes that accumulation rates were constant between neighbouring dated depths and changed, potentially abruptly, exactly at the dated depths (Bennett, 1994). We then applied a classical model that varies more smoothly over time (smooth spline in \textit{clam}). Since ages further down a core must be older, even if the dates or models suggest otherwise, software implementing the above approaches can be instructed to remove any iterations with age-depth model reversals after modelling. Finally, we tested two
Bayesian piecewise linear models that use gamma distributions as prior information in order to ensure chronological ordering of the age-depth models. *Bchron* (Haslett and Parnell, 2008) simulates steps in time and depth sampled from gamma distributions, whereas *Bacon* (Blaauw and Christen, 2011) models the accumulation rates of many equally spaced depth sections based on an autoregressive process with gamma innovations (here set at mean 50 and shape 1.1 to allow for many accumulation rates), and a beta distribution to invoke a degree of dependence in accumulation rate between neighbouring depths. Both *Bchron* and *Bacon* have routines to handle outliers, whereas for classical age-depth models outliers need to be removed manually. OxCal’s $P_{\text{sequence}}$ (Bronk Ramsey, 2008) was also tried but individual runs and analyses interpolated to 500 1-cm intervals took days instead of minutes, rendering it less suitable for these intensive simulation exercises. R (R Core Team, 2017) code of the *simacc*, *simdat* and *simage* simulations is available on Figshare (doi:10.6084/m9.figshare.3808311).

All age-depth models were produced as outlined above. Precision was calculated as 95% confidence ranges for the age estimates of each depth of a core, after which the minimum, maximum and mean confidence ranges were stored. For cores where ‘true’ accumulation histories were known (Holzmaar and *simacc* simulations), each age-depth model *simage* was compared to the known age $\theta_d$ for each depth $d$. Accuracy was then calculated as standardized offset, $z_d = |\bar{x}_d - \theta_d|/\sigma_d$, where $\bar{x}_d$ and $\sigma_d$ are the mean and standard deviation, respectively, of the modelled ages. Standardizing ensures that offsets can be compared between core depths modelled at different precisions. Then the minimum, maximum and mean $z$ over all core depths was taken as the age-depth model’s accuracy. In this context, precision refers to the degree of uncertainty in an age estimate and accuracy refers to the difference between the estimated and true values.
RESULTS

Depending on their dating density and the chosen age-depth model type, chronologies for cores from the Neotoma database reach millennial to centennial-scale precision (Figure 1), and the same holds for sequential re-dating of Kråkenes (Figure 3). At first sight, the commonly used classical age-depth models based on linear interpolation or smooth splines (Bennett, 2007; Blaauw, 2010) appear to produce more precise chronologies than do the Bayesian models, namely \textit{Bchron} and \textit{Bacon} (Haslett and Parnell, 2008; Blaauw and Christen, 2011). These narrow estimates of precision, even at low dating densities, are due to the implicit assumption that the chosen age-depth model is the true one, so the model has zero error for the choice of age-depth model. At below-average dating densities, adding dates enhances the precision of classical age-depth models, but this effect levels off at average and higher dating densities. Bayesian age-depth models on the other hand consistently become more precise as dating density increases.

Precision is not the only measure to judge an age-model. Hence where ‘true’ accumulation histories were available (Holzmaar, sim\_acc simulations), we calculated both precision and accuracy (Figure 5 and Supplementary information animations 1–4). At the initial, lowest dating densities, most age-depth models fail, unsurprisingly, to capture the long-term shapes of the simulated age-depth trajectories (Telford et al., 2004; Trachsel and Telford, 2017) even though the 95\% confidence intervals of the Bayesian models mostly overlap with the ‘true’ ages. As a few more strategically chosen dates are added, all models improve to follow a site’s main features. However what happens at higher dating densities depends largely on the chosen age-depth model type.

Our analyses of Holzmaar and the sim\_acc simulations reveal several important implications of different approaches to age-depth modelling. As with the cores from the Neotoma database and Kråkenes, different model types produce very
different precision estimates (Figure 5a, c, e, g). The classical models of linear interpolation and smooth spline again appear at first sight to be pleasingly precise (average 95% ranges mostly under ca 500 yr), due to the implicit zero error for choice of age-depth model (see above). It is crucial to note that the supposedly high precision of classical age-depth models comes at a severe cost; they are inaccurate especially at low to average dating densities. Indeed, at those dating densities classical (especially linear interpolation) age-depth models are offset from the ‘true’ ages by many standard deviations; Figure 5b, d). On the other hand, the Bayesian age-depth models reconstruct much larger uncertainties especially at low to average dating densities (up to 1 dpm). They are consistently accurate and produce realistic estimates of precision, the true ages lying well within two standard deviations (95%) at most depths and dating densities (Figure 5f, h). Even so, in all of our simulations (classical and Bayesian) and at almost all dating densities, the 95% confidence ranges of some depths lie outside their ‘true’ ages (envelopes extending above the 2 sd limit in Figure 5).

Above ca 1 dpm, linear interpolation age-depth models do not become more precise at increasing dating densities, whereas the smooth-spline models show some improvement after reaching ca 5 dpm. However, the Bayesian models continue to improve. This is because the Bayesian models we are considering (Bchron and Bacon) take advantage of chronological ordering, causing ever-increasing precision (yet remaining accurate) as more and more dates start to overlap. At dating densities high enough to match the multi-decadal wiggles in the $^{14}$C calibration curve (Kilian et al., 1995; Gulliksen et al., 1998; Lohne et al., 2013; Mauquoy et al., 2002; Blaauw et al., 2004; Southon et al., 2012) (Figure 6), some sections of Bayesian models can reach multi-decadal precision. Above 30-50 dpm even classical models gain precision again as repeated dating of individual depths enhances their age estimates.

The relationship between dating density and model precision and, especially, accuracy is not entirely monotonic. Sometimes adding a few extra dates will
provide an extra piece of information that suddenly results in much more
precise and/or accurate chronologies. However the opposite can also happen
when, for example, adding an extra date causes an age reversal with classical
age-depth models, or an outlying date produces a less accurate model
(particularly for linear interpolation, which is highly sensitive to outliers).

Our simulations of linear interpolation and Bacon show a clear impact of error
size on age-depth model precision but not accuracy (Figure 7). Dating scatter
(Christen and Pérez E., 2009; Scott, 2013) on the other hand appears to have
little impact on age-depth model precision (no impact for linear interpolation
and a minor one for Bacon), but it severely impacts accuracy. Model offsets
from ‘true’ ages increase along with increasing scatter, although Bacon’s
offsets are always considerably lower than those of linear interpolation.
Similarly to dating scatter, outliers have little to no impact on model precision
while severely affecting accuracy (Figure 7i–l). Most classical age-depth
models are offset by two or more standard deviations once more than 20% of
the dates are outlying, while Bacon, remarkably, remains accurate until over
50% of dates are outlying.

IMPLICATIONS

In the early days of \(^{14}\)C dating, dating densities of cores were necessarily low
because slices covering many centimetres or even decimetres (and thus
centuries of sedimentation) had to be submitted to obtain sufficient datable
\(^{14}\)C for the conventional decay counting method (e.g. Bennett et al., 1992;
Haberle and Lumley, 1998). With the advent of AMS dating in the 1990s this
limitation has largely been lifted. Prices of single dates have also come down in
real terms. However median dating density remains below 1 dpm (Figure 1),
perhaps because the research community still considers 1 dpm to be a
reasonable rule-of-thumb in order to establish chronologies, or because funding
for chronologies has not increased (with the exception of special cases where
chronology is the emphasis of the study). Our simulations show, however, that
typical dating densities are insufficient and that, at these densities, classical
age-depth models may fail to capture the main features of a site’s
accumulation history and produce highly over-optimistic precision estimates
(Figure 4). Increasing the dating density to ca 2 dpm, and using Bayesian
chronology building methods such as *Bchron* or *Bacon*, produces age-depth
models that give reasonable confidence for centennial-scale precision estimates.
If sub-centennial chronological precision is needed (at least for selected core
sections; Figure 6), dating densities over 50 dpm are required, together with
age-depth models that take advantage of chronological ordering. Thus,
chronologies should be built starting with a skeleton chronology of, say, 1 date
every 2 millennia (0.5 dpm), after which small batches of strategically sampled
depths should be dated sequentially until reaching ca 2 dpm (or higher
depending on the required precision). This will require a modest increase in
funds for dating (though costs will still be minor compared to other costs of
most investigations) and higher usage of available Bayesian age-depth models,
but will provide the accuracy and precision needed to interpret and correlate
chronologies at the level required for most palaeoenvironmental questions.

Dating scatter seems more disruptive to age-depth model accuracy than error
size (Figure 7), so it makes more sense to re-date single depths (e.g., to assess
the reliability of dating different components) or date multiple depths
(constraining the ages of individually dated depths through enforcing
chronological ordering), rather than obtaining fewer high-precision dates.

Over past decades, the palaeoenvironmental community has repeatedly been
warned to take uncertainties into account (Maher, 1972; Bennett, 1994;
Blaauw et al., 2007; Blaauw, 2010; Jackson, 2012). Classical age-depth
modelling approaches such as linear interpolation remain widely accepted and
used without paying much critical attention to their supposed precision.
Shurtliff et al. (2017) argue for “linear interpolation to be as good an approach
as any”, since “all age-depth models contain considerable uncertainty that is
difficult to fully quantify”. However, simulations such as ours do help to
quantify such uncertainties, and as a community we should ask ourselves
whether classical age-depth models remain suited to their task (Bennett, 1994;
Telford et al., 2004; Trachsel and Telford, 2017). The method of linear
interpolation suggests higher precision in-between dated depths, and becomes
more precise with larger gaps between dated depths (Bennett, 1994). This
counterintuitive result arises because this model implicitly assumes (i) that
this is the true model, although we know that it is not; and (ii) that ages
between dated points lie along a straight line, which is rarely, if ever, going to
be true. Relaxing the assumption (e.g., with Bayesian methods such as
Bchron and Bacon) produces the more intuitive result that sections with
fewer dates reach lower precision. The Bayesian models excel since they
simulate many different alternative ‘routes’ by which a site could have
accumulated in-between dated depths, diverging more from the
linearly-interpolated relationship if less ‘guidance’ is present.

Even at low to average dating densities, Bayesian models such as Bchron or
Bacon are preferable to classical models, since their model assumptions
produce more realistic reconstructions and confidence intervals. At higher
dating densities, the dates start to steer the models more directly and the
accuracy of classical and Bayesian models is comparable — though Bayesian
models that enforce chronological ordering can become much more precise.

ACKNOWLEDGEMENTS

This work was partly funded by a Banco Santander travel grant to MB.
Thanks to Andrew Parnell for help with Bchron and to Simon Goring for
releasing R code to extract sites from the Neotoma Paleoecology database
(http://www.neotomadb.org); the work of the data contributors and the
Neotoma community is gratefully acknowledged. We are also grateful to the
Past Earth Network (http://www.pastearth.net/) for writing support (grant
number EP/M008363/1).

References

Bennett, K. D., 1994. Confidence intervals for age estimates and deposition
times in late-Quaternary sediment sequences. The Holocene 4, 337–348.

Bennett, K. D., 2007. psimpoll and pscomb programs for plotting and analysis.
URL http://www.chrono.qub.ac.uk/psimpoll/psimpoll.html

history of environment, vegetation and human settlement on Catta Ness,

Bennett, K. D., Buck, C. E., 2016. Interpretation of lake sediment
accumulation rates. The Holocene 26, 1092–102.

Bennett, K. D., Fuller, J. L., 2002. Determining the age of the mid-Holocene
Tsuga canadensis (hemlock) decline, eastern North America. The Holocene
12, 421–429.

Blaauw, M., 2010. Methods and code for classical age-modelling of
radiocarbon sequences. Quaternary Geochronology 5, 512–518.

Quaternary Science Reviews 36, 38–48.

Blaauw, M., Christen, J. A., 2011. Flexible paleoclimate age–depth models
using an autoregressive gamma process. Bayesian Analysis 3, 457–474.

Blaauw, M., Christen, J. A., Manquoy, D., van der Plicht, J., Bennett, K. D.,
2007. Testing the timing of radiocarbon-dated events between proxy
archives. The Holocene 17, 283–288.

Birks, H. J. B., Juggins, S., Lotter, A., Smol, J. P. (Eds.), Tracking
Environmental Change Using Lake Sediments, Developments in

change during the mid-Holocene: indications from raised bogs in The
Netherlands. The Holocene 14, 35–44.

Building and testing age models for radiocarbon dates in Lateglacial and

Quaternary Science Reviews 27, 42–60.


Christen, J. A., Sansó, B., 2011. Advances in the sequential design of
computer experiments based on active learning. Communications in
Statistics — Theory and Methods, 4467–4483.

Goring, S., Dawson, A., Simpson, G. L., Ram, K., Graham, R. W., Grimm,
E. C., Williams, J. W., 2012. neotoma: A programmatic interface to the
Neotoma Paleoeccological Database. Open Quaternary 1 (2).

Groot, M. H. M., van der Plicht, J., Hooghiemstra, H., Lourens, L. J., Rowe,
methods from the Andean Fúquene Basin (Colombia) case study.
Quaternary Geochronology 22, 144–154.

estimate of the Younger Dryas–Holocene boundary at Kråkenes, western
Norway. The Holocene 8, 249–259.

Haberle, S. G., Lumley, S. H., 1998. Age and origin of tephras recorded in
postglacial lake sediments to the west of the southern Andes, 44°S to 47°S.
Journal of Volcanology and Geothermal Research 84, 239–256.

Haslett, J., Parnell, A. C., 2008. A simple monotone process with application
to radiocarbon-dated depth chronologies. Journal of the Royal Statistical
Society, Series C 57, 399–418.

Jackson, S. T., 2012. Representation of flora and vegetation in Quaternary
fossil assemblages: known and unknown knowns and unknowns. Quaternary

aspects of AMS $^{14}$C wiggle matching, a reservoir effect and climatic change.
Quaternary Science Reviews 14, 959–966.

Lohne, Ø. S., Mangerud, J., Birks, H. H., 2013. Precise $^{14}$C ages of the Vedde
and Saksumarvatn ashes and the Younger Dryas boundaries from western
Norway and their comparison with the Greenland Ice Core (GICC05)

County, Colorado. Quaternary Research 2, 531–553.

from northwest European bogs shows ‘Little Ice Age’ climatic changes
driven by variations in solar activity. The Holocene 12, 1–6.


Trachsel, M., Telford, R. J., 2017. All age–depth models are wrong, but are getting better. The Holocene 27, 860–869.

Figure 1: Dating density (dates per millennium) and age-depth model precision (95% error ranges) of all 356 $^{14}$C-dated cores containing pollen counts and spanning at least 500 yr and having at least 2 $^{14}$C dates, extracted from the Neotoma Database using R code (Goring et al., 2012). Left panel shows classical age-depth models (red linear interpolation, blue smooth spline), right panel shows Bayesian age-depth models (red Bacon, blue Bchron). Vertical lines indicate the minimum to maximum age-depth model precision of each core; dots or crosses indicate means. Note logarithmic axes.
Figure 2: Flow diagram of the dating, age-depth modelling and analysis of existing cores (Neotoma, Kråkenes and Holzmaar) and simacc simulations. Precision estimates are calculated for each age-depth model as the minimum, mean and maximum 95% confidence intervals. The impacts of adding dates on age-depth model precision are investigated using simdat (not for Neotoma sites). Accuracy, as the standardized offset between a model and the ‘true’ underlying accumulation history, can only be calculated for Holzmaar and simulated accumulations simacc.
Figure 3: Dating density (dates per millennium) and age-depth model precision (95% error ranges) upon sequential re-dating of the high-resolution dated Kråkenes record (Gulliksen et al., 1998; Lohne et al., 2013). Left panel shows classical age-depth models (red linear interpolation, blue smooth spline), right panel shows Bayesian age-depth models (red Bacon, blue Bchron). Shaded envelopes and dashed curves show minimum to maximum resp mean age-depth model precision. Note logarithmic axes.
Figure 4: The three stages of sedimentation, sequential dating, and age-depth modelling. The upper panel shows six \textit{simacc} simulations using a range of random seeds (1: 5113, 2: 2995, 3: 5993), a smooth spline (\textit{smspl}) through the “Example” core provided with \textit{clam} (Blaauw, 2010) (orange), simulation 11136 (Younger Dryas) and simulation 1102 (at the ca. 3-2 kcal BP Hallstatt Plateau). Dotted curve is from varved Lake Holzmaar (Zolitschka et al., 2000).

The lower panel shows the sequential process of selecting which depth to date next, producing the resulting age-depth model, and comparing the model to the known ages. In this example, so far four depths have been dated (blue silhouettes; \textit{sim_dat}) from the simulated core (red curve; \textit{simacc}). A smooth-spline age-depth model is drawn through these dates (grey envelope and dashed black line; \textit{sim_age}). Its age estimates can be compared to the ‘true’ history (red).

From the sample spacing and the age-depth model’s variance and covariance at each depth a sampling score is calculated (green distribution). The depth of 1 m has the highest score (dashed green line) and will thus be dated next.
Figure 5: Impact of dating density on chronological precision and accuracy using classical (a-b, linear interpolation; c-d, smooth spline) and Bayesian (e-f, Bacon (Blaauw and Christen, 2011); g-h, Bchron (Haslett and Parnell, 2008)) age-depth models. For each of 4 simulated cores and the Holzmaar record (see Figure 4 for key to colours), dates were added sequentially (simdat, up to 10 dpm) and age-depth models constructed (simage). Curves show mean values and envelopes show minimum to maximum values for age-depth model precision (95% error ranges, left panels) and accuracy (standardized offset from ‘true’ ages, right panels; dashed curve shows 2 standard deviation offset). Because smooth splines require at least 4 dates, panels c and d only show precision or accuracy estimates for dating densities above c. 0.3 dpm. Since the Holzmaar curve closely resembles that of the simacc simulations, the latter are likely to represent realistic accumulation histories. Note logarithmic axes.
Figure 6: Impact of high dating densities on model reliability at periods with major wiggles in the IntCal13 $^{14}$C calibration curve (Reimer et al., 2013) for a range of age-depth model types (a-b linear interpolation, c-d smooth spline, e-f Bacon (Blaauw and Christen, 2011), g-h Bchron (Haslett and Parnell, 2008)). Red curves indicate simulation 11136 (see Figure 3) focusing on the Younger Dryas Period; blue curves show simulation 1102 around the ca. 3-2 kcal BP Hallstatt Plateau. Precision and accuracy are shown in left and right panels, respectively. At high dating densities, single depths are dated several times, causing conflicting age estimates and resulting in unsuccessful Bchron runs for the YD simulation. Note logarithmic axes.
Figure 7: Impact on precision (left panels) and accuracy (right panels) of laboratory error (a-d), dating scatter (e-h) and outliers (i-l) on model reliability. Curves show mean precision and accuracy at a range of dating dates per millennium (see legend in panel a). Given the time-consuming nature of these simulations, results are available only for linear interpolation and Bacon.