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The Temporal Phasing of Rapid Dansgaard–Oeschger Warming Events Cannot Be Reliably Determined

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Abstract. Dansgaard–Oeschger (DO) warming events occurred throughout the last glacial period. Greenland ice cores show a rapid warming during each stadial to interstadial transition, alongside abrupt loss of sea ice and major reorganisation of the atmospheric circulation. Other records also indicate simultaneous abrupt changes to the oceanic circulation. Recently, an advanced Bayesian ramp fitting method has been developed and used to investigate time lags between transitions in these different climate elements, with a view to determining the relative order of these changes. Here, we subject this method to a critical review. Using ice core data, climate model output, and carefully synthesised data representing DO warming events, we demonstrate that the method suffers from noise-induced bias of up to 15 years. This bias means that the method will tend to yield transition onsets that are too early, and we find that the estimated timings of noisier transitions are more strongly biased. Further investigation of DO warming event records in climate models and ice core data reveals that the bias is on the same order of magnitude as potential timing differences between the abrupt transitions of different climate elements. Additionally, we find that higher-resolution records would not reduce this bias. We conclude that time lags of less than 20 years cannot be reliably detected, as we cannot exclude the possibility that they result solely from the bias. This prevents the unambiguous determination of the temporal phasing of DO warming events.

1 Introduction

Proxy records from Greenland ice cores provide evidence for millennial-scale climate variability throughout the last glacial period (Dansgaard et al., 1982; Johnsen et al., 1992; Dansgaard et al., 1993; NGRIP members, 2004). The most striking feature of this variability is the repeated occurrence of Dansgaard–Oeschger (DO) warming events, during which Greenland temperatures increased by up to 15 degrees in just a few decades (Steffensen et al., 2008; Kindler et al., 2014; Capron et al., 2021) as Greenland rapidly transitioned from a cold stadial to a warm interstadial state. Alongside this rapid warming in Greenland, there is evidence for abrupt retreat of sea ice in the North Atlantic and Nordic Seas (Li et al., 2005, 2010; Dokken et al., 2013; Hoff et al., 2016; Sime et al., 2019; Maffezzoli et al., 2019; Sadatzki et al., 2020), and a reinvigoration of the Atlantic

Meridional Overturning Circulation (AMOC) from a rather weak stadial to strong interstadial state (Gottschalk et al., 2015; Henry et al., 2016; Lynch-Stieglitz, 2017). Furthermore, beyond the North Atlantic, a number of paleoclimate archives provide evidence for global-scale reorganisations of the atmospheric circulation (Markle et al., 2017; Schüpbach et al., 2018; Buizert et al., b; Erhardt et al., 2019) including a northward displacement of the inter-tropical convergence zone (ITCZ) (Schneider et al., 2014) and changes in global precipitation patterns (Fohlmeister et al., 2023). The latter are particularly well documented in the Asian (Wang et al., c, b; Li et al., 2017) and South American Monsoon regions (Wang et al., a; Kanner et al., 2012; Cheng et al., 2013), as well as the European–Mediterranean region (Drysdale et al., 2007; Fleitmann et al., 2009; Moseley et al., 2014; Corrick et al., 2020). However, as of yet it has not been possible to conclusively identify a cause for these rapid Dansgaard–Oeschger warming events. These periods of abrupt warming in the North Atlantic can be considered as but one of four parts in a larger DO cycle (Lohmann and Ditlevsen, 2019). Consistent with previous studies (Adolphi et al., 2018; Corrick et al., 2020, *e.g.*), we do not consider the whole cycle but only the various abrupt changes that occurred during the stadial to interstadial transitions. Henceforth, we refer collectively to these abrupt changes simply as DO events.

One paradigm in which we can consider DO events is as cascades of sudden changes in different climate variables. From this perspective, an analysis of the temporal order of events, in models or in the paleoclimate record, should unravel the mechanistic dynamics of DO events. Previous research has attempted to identify temporal lags between the sudden changes in different climate components associated with DO events by comparing the DO event ages inferred from Greenland ice core records with the ages of corresponding sudden shifts in speleothem records from lower latitudes and change points evident in Antarctic ice core records (Buizert et al., a; Adolphi et al., 2018; Corrick et al., 2020; Svensson et al., 2020). A second line of research has focused on the analysis of multi-tracer records from Greenland (Steffensen et al., 2008; Erhardt et al., 2019; Capron et al., 2021; Riechers and Boers, 2021). This has the advantage that jointly measured proxy variables usually reflect the state of different components of the climate system free of any relative dating uncertainty. However, both approaches face the challenge of inferring transition times from noisy data.

On the first line of evidence, Adolphi et al. (2018) applied a Bayesian ramp fitting method, developed and later presented by Erhardt et al. (2019), to compare the ages of DO events evident in speleothem records with those identified in the NGRIP ice core record. The authors concluded that high and low latitude climatic changes at DO events happened simultaneously, within uncertainty of around a century. This work hinged on a synchronisation of the NGRIP chronology to previously identified tie-points to independently dated records. Corrick et al. (2020) then assessed a larger set of speleothem records. Like Adolphi et al. (2018), they also found that high and low latitude climate change happened synchronously. These authors used a different method for estimating the DO event ages in both the speleothem data and the NGRIP ice core data, basing their assessment on the original NGRIP chronology rather than the synchronised one. Although both studies reach the conclusion that the abrupt changes occurred simultaneously at high and low latitudes, they contradict each other regarding the timing of the DO events.

On the second line of research, Erhardt et al. (2019) employed their advanced Bayesian method, to determine the transition onset times for DO events using multiple proxies in Greenland ice cores. Stacking multiple DO events in a multi-proxy analysis of Greenland ice core data, Erhardt et al. (2019) identified time lags between the different proxies. Considering DO events

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back to 60,000 years before present, the authors concluded that atmospheric changes preceded the reduction in sea ice extent by around a decade.

Subsequent to this work, Riechers and Boers (2021) found that these time lags are not statistically significant, when all of the relevant sources of uncertainty are rigorously propagated. Capron et al. (2021) followed up on this by extending a similar multi-proxy analysis of Greenland ice core data back to 120,000 years ago. In agreement with Riechers and Boers (2021), they also concluded that applying a method of the type developed by Erhardt et al. (2019) to ice core data may not allow the identification of a unique order. Capron et al. (2021) suggest that this is due to the tight coupling of the different climate elements, alongside substantial variability between different DO events.

Intriguingly, thanks in part to advances in model development alongside computing power, spontaneous DO-like millennial variability is now captured by least six General Circulation Models (Brown and Galbraith, 2016; Vettoretti and Peltier, 2016; Klockmann et al., 2020; Zhang et al., 2021; Kuniyoshi et al., 2022; Malmierca-Vallet et al., 2023). The millennial variability is spontaneous in the sense that it is not externally forced by changes to atmospheric carbon dioxide concentrations or orbital parameters or by freshwater hosing. Whilst we may assume these model simulations are imperfect representations of real DO events, nonetheless they provide an invaluable means to help us investigate the question of whether it is possible to conclusively identify a cause for rapid Dansgaard–Oeschger warming events. This is because they provide complete information about the temporal order of changes in different components of the climate. We can therefore use them to test means of determining the cause, and order, of events during DO-like warming events.

Here, we build upon these recent advances, examining in detail the causes of uncertainty and the question of what can therefore be learned from paleo-archives about the onset time of DO events in different climate elements - or proxies for these - such as temperature, precipitation, atmospheric circulation, sea ice, and AMOC. This also enables us to comment on whether it may be possible to determine the order of changes within a DO cascade. Our manuscript firstly extends and critically reviews the Bayesian ramp fitting method provided by Erhardt et al. (2019), investigating whether the method is biased depending on the characteristics of a given transition as well as possible approaches to bias correction for application to real-world data. Secondly, we apply this method to data from the CCSM4 model (Vettoretti et al., 2022), chosen because the CCSM4 simulated DO events closely match real DO events in terms of their magnitude of Greenland warming, the duration of stadial and interstadial periods, and the bipolar seesaw relationship between Greenland and Antarctica. Thirdly, we revisit the original Greenland multi-proxy data from ice cores and comprehensively investigate relevant biases. Finally, we discuss the implications of our findings for whether the temporal phasing of DO events can be determined from paleo-data.

2 Data & Methodology

2.1 Model Data

The Spontaneous Dansgaard-Oeschger type Oscillations in climate models (SDOO) project, under the EU-TiPES program, gathers together available simulation output from models which show DO like oscillations (Malmierca-Vallet et al., 2023, https://www.bas.ac.uk/project/sdoo/#data;). Included in this data-set are decadal mean output from six CCSM4 model runs

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which Vettoretti et al. (2022) have kindly provided. Each of these six simulations is 8000 years long, and exhibits DO-like behaviour, including DO-like warming events which closely matches DO like behaviours recorded in paleo-data. The runs are forced using last glacial maximum boundary conditions (Vettoretti et al., 2022) alongside varying concentrations of atmospheric carbon dioxide, from 185 to 230 ppm. This range closely matches the atmospheric carbon dioxide concentrations during Marine Isotope Stage 3, when DO events were most frequent (Malmierca-Vallet et al., 2023). The number of events in each run appears to depends on the chosen CO_2 concentrations, with highest DO frequency at 200ppm. Outside of the chosen range of CO_2 concentrations the model does not show any such events (Vettoretti et al., 2022). In total, there are 19 abrupt warming events in these six simulations.

We select five variables from CCSM4 in order to compare the timing of their relative transitions. These are North Atlantic Surface Air Temperature, Precipitation, and Sea Ice Extent, as well as the North Atlantic Oscillation (NAO), and the Atlantic Meridional Overturning Circulation (AMOC). The first four of these are chosen as they have previously (Capron et al., 2021) been identified with four proxies that can be measured in ice cores (for the identification of model variables and ice core proxies see Table 1). We added the AMOC to this selection due to the integral part it is thought to play in DO events (*e.g.* Lynch-Stieglitz, 2017; Li and Born, 2019; Malmierca-Vallet et al., 2023). We calculate time series for Temperature, Precipitation, and Sea Ice by taking area-weighted means over a selected region of the North Atlantic (shown in Fig. 4). AMOC is given by the spatial maximum of the stream-function in the North Atlantic between 20° and 60° North at any depth. The NAO index is calculated as the first principal component of sea level pressure across the region 30° - 80° North and 80° West to 40° East.

From the resulting time series, we visually identify the abrupt warming events. For the analysis we isolate the individual events in data windows of 800 years approximately centred on the transition. To ensure consistency, these same search windows are used for all five variables of interest.

Alongside the full data-set that is available at 10-year resolution, there are a small number of annually-resolved simulations. Although not sufficient to assess potential systematic time lags, these roughly indicate the possible parameter ranges at this higher resolution, and so allow us to gain an insight into how increased resolution impacts the bias in the ramp fitting method.

2.2 Ice Core Data

Alongside the model data, we also revisit data from the North Greenland Ice Core Project (NGRIP) ice core (NGRIP members, 2004) that were previously analysed using this method (Erhardt et al., 2019). We make use of the data provided by Erhardt et al. for four proxies from this core over 16 stadial-interstadial transitions ranging in time from the Holocene onset to the onset of Greenland Interstadial 17.2 at around 60,000 years before present. Whilst Erhardt et al. applied the ramp fitting method to a larger set of transitions, these 16 are the only ones for which there were no data gaps and for which the method was successful for all four proxies.

The four proxies in this data-set are $\delta^{18}O$, annual layer hickness, concentration of dust aerosol (Ca ions), and concentration of sea salt aerosol (Na ions). These four proxies are respectively interpreted as representing the air temperature at the core site, precipitation at the site, large-scale Northern Hemisphere atmospheric circulation, and sea ice extent in the oceans around Greenland (Erhardt et al., 2019). These one-to-one identifications of proxies with individual climate elements a major sim-

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Table 1. A summary of the model and ice core data employed in this study. Each row indicates the identification of a particular ice core proxy with a particular model output variable, following Capron et al. (2021).

CCSM4 Variable	Resolution / Years	NGRIP Proxy	Resolution / Years
Temperature	10	$\delta^{18}O$	4 – 7
Precipitation	10	Annual Layer Thickness	2 – 3
Sea Ice	10	Na	2 – 3
NAO	10	Ca	2 – 3
AMOC	10	N/A	N/A

plification. For example, $\delta^{18}O$ is also strongly influenced by changes in sea ice extent in the region around Greenland (Sime et al., 2019). For in-depth discussion of the physical interpretation of these proxies, see Section 2 of Erhardt et al. (2019) and references therein. As our focus in this work is on the ramp fitting method itself more so than the data that we are applying it to, we uncritically adopt the previous identification of proxies with individual climate elements despite the limitations of this approach.

The aerosol concentrations were measured using Continuous Flow Analysis (CFA) at temporal resolution ranging from 2 years for the most recent period to 3 years for the oldest period. The resolution for the $\delta^{18}O$ measurements increases from 4 years to 7 years. The time series used in this study are approximately 500-year long sections over each DO event. The annual layer thickness record has been down-sampled to match the resolution of the CFA data. Both the model data and ice core data employed in this study are summarised in Table 1.

2.3 Ramp Fitting Method

To determine the timing of each warming event we use an adapted version of the method presented by Erhardt et al. and previously applied to DO events recorded in ice cores and speleothems (Adolphi et al., 2018; Erhardt et al., 2019; Capron et al., 2021). In short, the method relies on a deterministic linear transition model between two equilibria of the form

$$x(t) = \begin{cases} x_0 & \text{for} \quad t < t_0 \\ x_0 + \frac{x_1 - x_0}{t_1 - t_0}(t - t_0) & \text{for} \quad t_0 < t < t_1 \\ x_1 & \text{for} \quad t > t_1. \end{cases} \tag{1}$$

The addition of an AR(1) noise process makes the model probabilistic and directly yields a Bayesian posterior distribution for the model parameters $\{t_0, t_1, x_0, x_1, \alpha, \sigma\}$, where α and σ define the autocorrelation and the amplitude of the noise.

In our application to the CCSM4 model data, some variables such as AMOC show an exaggerated “saw-tooth" shape, with a strong downward slope following the abrupt transition. This behaviour is not captured by the original Erhardt formulation,

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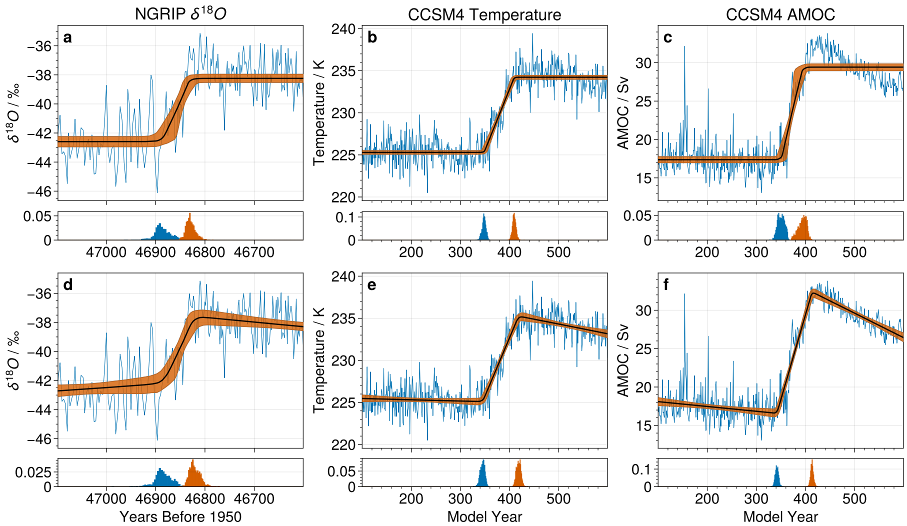

Figure 1. A comparison of the output when applying both the original flat version of the method (panels (a)–(c)) and the new slope version (panels (d)–(f)) to three different transitions. In panels (a) & (d), the two versions are applied to $\delta^{18}O$ from the NGRIP core (Erhardt et al. (2019) covering the transition to GI-12c. Panels (b) & (e) show surface air temperature at the nearest grid cell to the NGRIP site across a transition from CCSM4 (Vettoretti et al. (2022)), whilst c & f show AMOC for this same transition.

and so we extend the method by adding possible slopes before and after the linear ramp. This leads to improved agreement of the transition model with the analysed data (Figure 1). Additionally, our extension of the method reduces the sensitivity of the transition timing to the search window, which is otherwise one of the drawbacks of this method (Capron et al., 2021). For the full details of our updated method, see Appendix A.

2.4 Hypothesis Testing

We require a means by which to test the statistical significance of any time lags that we may discover in either the model or ice core data. Although the ramp fitting method is Bayesian, we adopt a frequentist perspective for our statistical analysis so as to be consistent with previous studies (Erhardt et al., 2019; Riechers and Boers, 2021).

For our analysis of the CCSM4 model, we define time lags for the transition onset of each of the other four variables relative to the transition onset in temperature T.

$$\Delta t^x = t_0^x - t_0^T. \tag{2}$$

A negative Δt^x thus corresponds to an earlier transition onset in variable x as compared to the temperature transition onset. We regard the Δt^x from the different simulated DO events as realizations of a repeated (identical) random experiment. This perspective allows the application of pairwise hypothesis tests. We then conduct pairwise hypothesis tests by comparing each of the other four variables to temperature using the following hypotheses:

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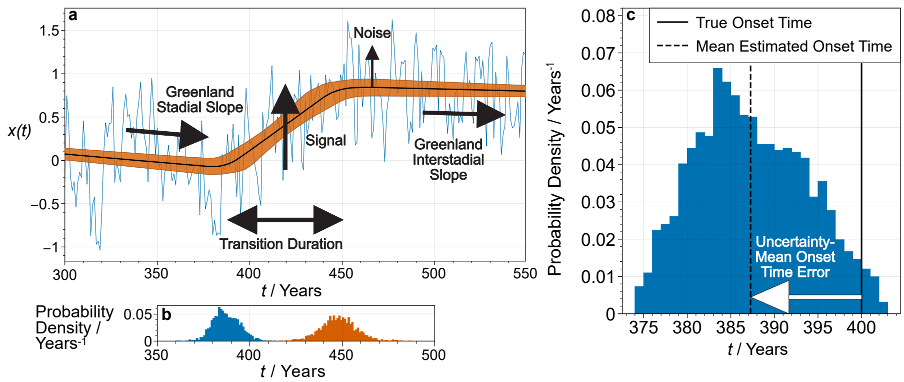

Figure 2. Panel (a): An example of a synthetic transition with annual resolution, and with the parameters of interest marked. Panel (b): The posterior distributions for the onset and end time of the transition. Panel (c): An enlarged reproduction of the posterior distribution for the transition onset time with the True Onset Time and Mean Estimate Onset Time shown. The True Onset Time (thick line) is set to be the year 400. The Mean Estimated Onset Time is the mean of the posterior distribution for the onset time t_0 produced by the application of the Bayesian ramp fitting method to this noisy data. The Uncertainty-Mean Onset Time Error (UMOTE) is given by the difference between these two times, and so a negative UMOTE, as seen here, indicates that the transition onset has been estimated to occur earlier than it truly does.

- H_0: $E[\Delta t^x] = 0$
- H_1: $E[\Delta t^x] \neq 0$

For the mathematical details of such a hypothesis test, see Appendix B.

We conduct our analysis of the NGRIP ice core in the same manner. In this instance, we calculate time lags for the other three proxies relative to Ca and conduct hypothesis tests as above.

$$\Delta t^x = t_0^x - t_0^{Ca}. \tag{3}$$

2.5 A Note on Nomenclature

In this work, we are dealing with two types of randomness. The first is the uncertainty in the determination of the transition time as reflected by Bayesian posterior distributions of the t_0 parameter. Secondly, as stated previously, we regard any set of abrupt transitions (be it in synthetic test data, GCM data or an ice core record) as repeated realisations of the same random experiment. The transition times of the different climate components assume the role of (correlated) random variables in this perspective.

Correspondingly, there are two types of averages that we use throughout this work. For sake of clarity, we refer to averages over Bayesian posterior distributions of parameters as *uncertainty-averages* or *uncertainty-mean*. Means over different realisations of the random experiment (i.e. over different events or transitions) are called *event-averages* or *event-means*.

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3 Results

3.1 Synthetic Transitions

As noted in the introduction, we wish to systematically test the ramp fitting method and investigate whether there are any biases in its estimation of transition timing. Indeed, we identify the following transition parameters (Figure 2) as potential sources of bias: (i) Noise / Signal Ratio (ξ), (ii) Autocorrelation Time of the Noise, (iii) Greenland Stadial Slope, (iv) Greenland Interstadial Slope, (v) Transition Duration.

To quantify the strength of the bias, we construct synthetic transitions according to the extended probabilistic transition model (see Appendix A). We consider transitions with temporal resolutions of 10 years (decadal) and 1 year (annual) in order to investigate the impact of different resolutions on the bias. In all cases, the synthetic transitions are 800 years long, with an abrupt warming transition that starts at the year 400. By comparing this true onset time to the uncertainty-mean onset time as estimated by the ramp fitting method, we calculate the Uncertainty-Mean Onset Time Error (UMOTE) for each synthetic transition (Figure 2). Though for an individual synthetic transition, the UMOTE is sensitive to the particular realisation of the AR(1) process. The event-average of the UMOTE with respect to the AR(1) noise can be identified with the bias of the method. Accordingly, we take a further event-mean over 100 separate synthetic transitions for each unique combination of parameter values.

The ranges over which the parameters are varied are chosen to reflect the ranges observed for these parameters when applying the ramp fitting method to different events and variables in the CCSM4 model simulations. The appropriate ranges for the Noise / Signal Ratio (ξ) and the Autocorrelation Time of the AR(1) noise differ between the cases of decadal and annual resolution because higher-resolution data is generally noisier. Note that the Greenland Interstadial Slope is negative in all cases, reflecting the classic "saw-tooth" shape of DO events, however we plot the absolute value of this slope for ease of legibility.

Our systematic testing of the ramp fitting method using synthetic transitions finds that the onset time estimate can be biased due to the transition parameters. Most importantly, there is generally a too-early bias of up to 10 years when the noise is high as shown by the blue region on the right-hand side of each panel in Fig. 3. We also find that the level of noise controls the strength of the impact of the other four parameters; when ξ is small, variations in the other parameters have little impact on the bias, but when this ratio is high variations in the other parameters have a large effect (~ 10 years). Focusing on the case of decadal resolution (panel (h)), for $\xi \sim 0.2$ an increase in the transition duration from 10 years to 100 years may even reverse the bias from ~ -10 years to $\sim +8$ years. It is therefore clear that the noise / signal ratio ξ is the key parameter in determining the bias of the ramp fitting method, but that the other parameters identified here also play an important role. Although the overall pattern is broadly similar between the cases of annual and decadal resolution, one notable difference is that the autocorrelation time significantly affects the bias at annual resolution, whereas this is not the case at decadal resolution.

As well as generally causing estimated transition onset times that are too early, a higher ξ also means that the estimated transition end times are too late. Because of this, there is a bias towards transition durations that are too long. This is important because this transition duration is itself one of the determining factors of the bias in the transition onset time. We will see in Section 3.3 that this limits our ability to correct for the bias we have described here.

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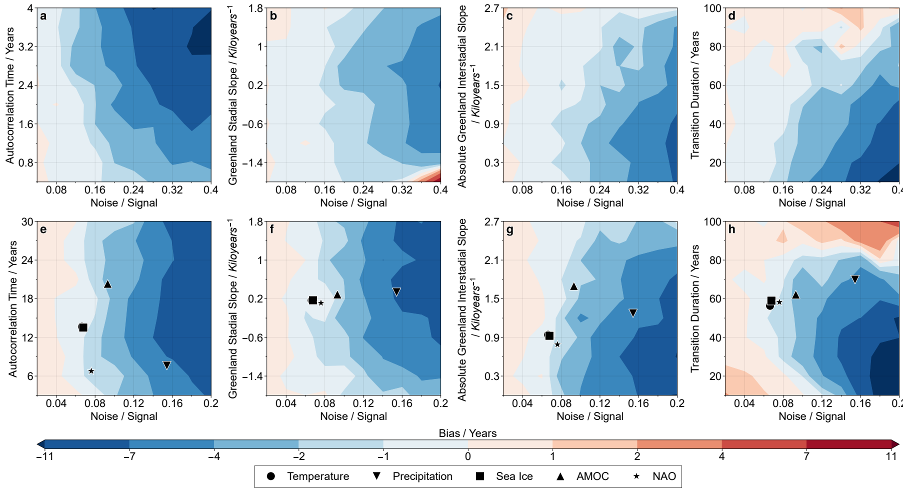

Figure 3. The bias in the transition onset time, as a function of the five transition parameters. Panels (a)–(d) show the bias for synthetic transitions of annual resolution, whilst (e) – (h) show the same for decadal resolution. Blue colours indicate a bias towards transition onset times that are too early, with red indicating the opposite. The mean transition parameters for the five variables of interest in the CCSM4 model (at decadal resolution) are overlaid on panels (e)–(h).

Further systematic testing reveals that such bias persists, though somewhat altered, when adopting an alternative set of prior probabilities (Fig. C2), when returning to the original Erhardt implementation of the ramp fitting method which lacks slopes before or after the transition (Fig. C3), or even when taking the simplest possible approach of a least-squares fit to a linear ramp (Fig. C4). The bias would therefore seem to be a robust observation that is not simply the result of our particular implementation of the ramp fitting method. Furthermore, to the best of our knowledge there is no unbiased method for estimating the onset time or transition duration that could be used for calibration or corroboration.

3.2 Impact of Changing Resolution

We are interested as to how the bias depends on the temporal resolution of the data. To investigate this, we create two further sets of synthetic transitions at annual resolution. These two sets represent the two contrasting cases of low-autocorrelation (“whiter") noise or high-autocorrelation (“redder") noise, with parameters chosen based on the extremes of the range observed in the CCSM4 model. For each of these synthetic transitions, we then down-sample to decadal resolution (Fig C5). For both types of noise we find that the bias is unchanged, within uncertainty, when switching between the two resolutions. These results are summarised in Table 2. We can therefore state that the temporal resolution has no impact on the bias, although higher resolution does at least reduce the uncertainty in the onset time estimates for individual transitions.

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Table 2. The bias for two different types of noise at both annual and decadal resolution, calculated from a sample of 1000 synthetic transitions. Uncertainties are given by the standard error on the sample mean.

Type of Noise	Annual Bias / Years	Decadal Bias / Years
Whiter	-3.1 ± 0.3	-3.4 ± 0.3
Redder	-7.2 ± 0.5	-7.0 ± 0.5

3.3 Bias in the CCSM4 Model and the Ice Core Record.

Following on from the above systematic testing, we investigate whether the ramp fitting method introduces any bias to the timing estimation of DO events in the CCSM4 model. To do this, we construct 1000 synthetic transitions that are "analogous" to each of the model variables of interest and assess the corresponding expected UMOTE as described above. The expected UMOTE serves as a first order approximation of the bias for each investigated climate variable and may thus be subtracted from the transition onset estimate obtain with the Bayesian ramp fitting method. The "analogous" transitions have noise and slope parameters that are representative of the appropriate variable, whilst retaining a fixed transition onset time and duration (50 years). We could instead use different, representative transition durations for each model variable. However, we have established that there is no unbiased means by which to estimate these transition durations, and so we could not guarantee that this would be any more accurate.

To calculate representative parameter values we take both the uncertainty-mean and the event-mean over the corresponding marginal posterior distributions obtained by applying the ramp fitting method to the 19 available transitions. For each variable or proxy this gives a single value for each transition parameter (shown in Fig. 3), which we use to create the "analogous" transitions.

The situation with precipitation is more difficult. Visual inspection of the precipitation time series reveals a much greater degree of noise during the stadials than the interstadials (Fig. C6). To test the impact of this, we investigate a further set of synthetic transitions which have two different noise regimes - one during the stadial and the other during the interstadial. We find that the value of ξ in the stadial is most important to the bias in the onset time (Fig C7). Because of this, creating synthetic transitions using a single noise regime is likely to underestimate the magnitude of the bias affecting precipitation, and so it is important that we include these two distinct levels of noise for precipitation. To do so, we further adapt the Bayesian ramp fitting method, producing a new version that treats noise before and after the transition separately. We find that this has a negative impact on the reliability of the method and so we do not use this updated version to assess timing. Instead, it simply provides a means of calculating appropriate parameter values to use for the synthetic transition that are "analogous" to precipitation. For completeness, the same analysis without accounting for these two noise regimes yields a bias that is reduced by almost 3 years (see Table 3).

Finally, we similarly investigate potential bias in the estimated transition timing of DO events in the NGRIP ice core. Here, we follow the same procedure as outlined above for CCSM4 model data. There is however an additional complexity due to the

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Table 3. Mean estimates and uncertainties for the biases affecting different variables in the CCSM4 model and different proxies in the NGRIP ice core, resulting from their differing noise characteristics. Each bias is calculated as the mean, across a sample of 1000 synthetic transitions, of the Uncertainty-Mean Onset Time Error (UMOTE, see Fig. 2). The uncertainty is given by the standard error on the sample mean of the UMOTE. The value is brackets for precipitation is the bias if we neglect the two separate noise regimes. As predicted, this is an under-estimate of the true bias.

CCSM4 Variable	Bias / Years	NGRIP Proxy	Bias / Years
Temperature	-1.0 $\pm$ 0.1	$\delta^{18}O$	-10.2 $\pm$ 0.5
Precipitation	-8.9 $\pm$ 0.4 (-6.0 $\pm$ 0.3)	Annual Layer Thickness	-6.0 $\pm$ 0.3
Sea Ice	-0.8 $\pm$ 0.1	Na	-9.4 $\pm$ 0.4
NAO	-1.2 $\pm$ 0.1	Ca	-4.8 $\pm$ 0.3
AMOC	-2.1 $\pm$ 0.2	N/A	N/A

differing time resolutions. For simplicity, we choose round numbers that are representative of the resolution of each proxy. We therefore use a resolution of 2 years for Ca, Na, and the annual layer thickness, and a resolution of 5 years for $\delta^{18}O$. Whereas for the CCSM4 model we used 800-year sections, here we create synthetic time series that are 500 years long, to match the ice core data. The true transition onset times are fixed to the year 250 and the transition durations are fixed at 50 years. The same difficulties around accurately estimating the transition duration that were discussed with respect to the CCSM4 model apply equally to this ice core.

The estimated biases for both the variables in the CCSM4 model and the proxies in the NGRIP ice core are listed in Table 3. Each row of this table reflects the association of particular ice core proxies and model variables, following Capron et al. (2021). Reflecting the general pattern found in Section 3.1, all of the variables and proxies are negatively biased, that is towards onset times that are too early. Importantly, the biases are different for different climate variables and hence they affect the assessment of temporal leads and lags between the corresponding transitions.

3.4 Time Lags in the CCSM4 Model in Light of the Bias.

In the following, we compare the transition onset times of the climate variables introduced in Section 2.1 at DO events simulated by the CCSM4 model. In doing so, we treat all simulated DO events equivalently, irrespective of the chosen CO_2 concentration. In particular, we take into account the bias which we quantified in the previous section. For each available DO event, we apply the Bayesian ramp fitting method to our selection of climate variables on the predefined data window.

For sea ice, AMOC, and NAO, we observe that the transition onsets occur approximately simultaneously with those in temperature, irrespective of the bias correction (Fig. 4), and so we do not discuss the hypothesis tests for these three variables. For precipitation the story is different. Without any bias correction the event-averaged time lag appears to be negative with certainty. Even under consideration of the bias, the uncertainty distribution of the precipitation-temperature lag is centred around

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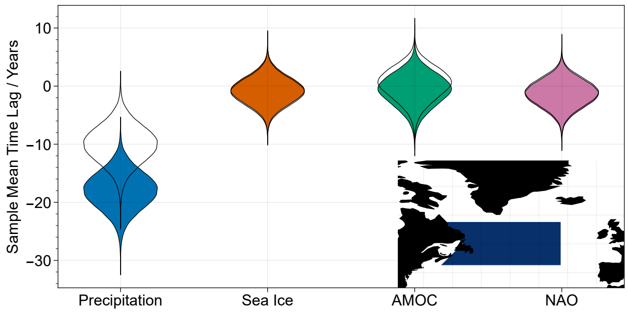

Figure 4. Uncertainty distributions for the uncorrected (filled) and bias-corrected (transparent) sample mean time lags of precipitation, sea ice, AMOC, and NAO as compared to temperature in the CCSM4 model. Inset is a map showing the region of the North Atlantic over which temperature, precipitation, and sea ice have been averaged. (Vettoretti et al., 2022).

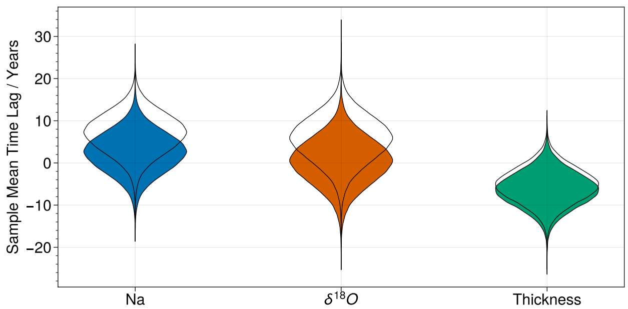

Figure 5. Probability distributions for the uncorrected (filled) and bias-corrected (transparent) sample mean time lags of Na, $\delta^{18}O$, and annual layer thickness as compared to Ca in the NGRIP ice core (NGRIP members, 2004; Erhardt et al., 2019)

-10 years with only small probabilities for a positive lag. This indicates that the transition onsets in precipitation are likely to occur before those in temperature. However, it is not clear whether this is statistically significant. Performing a hypothesis test as described in Section 2.4, we calculate a p-value of 0.078. As this is slightly greater than the standard significance threshold of 0.05, we cannot ultimately rule out the null hypothesis that the transitions in temperature and precipitation occur simultaneously.

3.5 Time Lags in the NGRIP Ice Core in Light of the Bias

Following the same procedure as for the model warming events, we calculate the sample mean time lags of Na, $\delta^{18}O$, and annual layer thickness, relative to Ca, in the NGRIP ice core. We again use the “analogous" synthetic transitions to perform a bias correction. Note that in this case each random sample is comprised of 16 of these synthetic transitions, as this is the size of our sample of DO events in the ice core. For each of these proxies, Fig. 5 clearly shows that the corrected distributions are consistent with zero time lag, and so we do not discuss the formal hypothesis tests.

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4 Discussion

We have demonstrated that the commonly used ramp fitting method is biased by up to 10 years when estimating the onset time of DO events. This is comparable to the magnitude of the time lags we might expect to find between different components of the climate (Erhardt et al., 2019), and so this bias severely limits the trust that we may have in any time lags identified in this manner. We have attempted, in Section 3.4, to correct for this bias in order to produce a more accurate estimate of the true time lags. In doing so, we found that even a large apparent time lag, such as the 18-year time lag we observed for precipitation in the CCSM4 model, could simply be the result of methodological bias.

Two key uncertainties enter into our hypothesis test for the significance of the difference in onset time between precipitation and temperature. These are the inherent uncertainty in the timing estimate of DO events and the uncertainty in the mean of a finite sample, which combine to form large uncertainties in both the observed and empirical null time lags. Considering this, the p-value of 0.078, though above the standard significance threshold of 0.05, may still appear rather small. This could suggest that the potential lead of precipitation merits further investigation. However, the standard significance threshold should really be adjusted downwards to correct for the fact that we have made multiple comparisons by comparing each of precipitation, sea ice, AMOC, and NAO to temperature. We do not feel the need to explicitly make this correction in this case because our finding is not significant even at the uncorrected threshold, and also because it is not clear precisely how this should be done. Nonetheless, this further strengthens the view that it is not possible to make any firm conclusion regarding the temporal phasing of DO events.

This is even more-so the case when we consider the major limitations of our bias-correction. The first of these is that we have followed the simplest possible approach of using single values for the parameters of our synthetic transitions. It would be more appropriate to instead sample from the range of parameter values exhibited by the same variable / proxy across different DO events. However, utilising the distribution of parameters in this way leads to estimates of the bias that are so uncertain as to lose meaning, and so we have used single parameter values (as given by combined uncertainty- and event- averages). Furthermore, the bias depends in a highly non-linear manner on interactions between the different transition parameters, and so our assumption that the bias resulting from the mean parameters is equal to the mean bias resulting from the whole range of parameters is a poor one.

Another issue is our inability to estimate the transition duration in an accurate manner. This has a major impact because the transition duration is a key determinant of the bias in the transition onset time, however the duration itself is also affected by this bias. We are thus stuck in an impossible situation whereby we cannot know the duration without first knowing the bias, but we simultaneously cannot know the bias without first knowing the duration. Because of this, the best we are able to do is to guess a plausible transition duration, for which we chose 50 years in all cases. The fact that these DO transition durations also cannot be determined is another important source of uncertainty that cannot be captured by a bias-correction procedure.

Given these limitations of the bias-correction procedure, there are clearly additional uncertainties affecting the time lags discussed in Sections 3.4 & 3.5 which we have not attempted to quantify. Even without incorporating these additional uncertainties, we reiterate that the identification of a statistically significant order to the DO events remains very challenging.

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Higher temporal resolution would allow us to somewhat reduce the uncertainty in the timing estimate of each DO event. But, as Section 3.2 shows, the temporal resolution of DO event paleo-data has no impact on the bias in the ramp fitting method. There is therefore limited prospect for improving this situation in the future through access to higher resolution model output data or indeed higher resolution paleo-measurements from ice cores.

5 Conclusions

Bayesian ramp fitting methods have shown great potential as a tool for identifying the temporal phasing of the changes in different climate components during climate transitions. For rapid DO warming, however, we demonstrate that even the advanced method of Erhardt et al. (2019) suffers from noise-induced bias when estimating the onset time of these very fast transitions. The bias ranges from approximately - 15 years to + 5 years, and so is comparable to or longer than the potential relative phasing of the climate elements that we seek to resolve. This severely limits the reliability of any time lags, whether in models or ice cores, that are found using this ramp fitting method. It is difficult to ascertain the magnitude of this bias in any individual case for any rapid DO warming events, and so any attempt to correct for the bias will necessarily introduce major additional uncertainty.

This leads to the conclusion that it may never be possible to confidently determine the order of Dansgaard-Oeschger warming events from these types of methods, no matter how many new ice cores are drilled or higher resolution measurements taken, because neither of these would alleviate the fundamental problem of bias in the method. In this, our work helps underpin the conclusion of Capron et al. (2021), who previously suggested that "it may be elusive to search for a single sequence of events". Despite the bias that we have uncovered here, we nevertheless suggest that this Bayesian ramp fitting method remains the best approach to understanding the temporal phasing of DO events. However, it appears impossible to reliably determine the temporal phasing when dealing with time lags that are less than around 20 years, i.e. it is not possible to successfully apply this method to determine the temporal phasing of DO warming events. This does not necessarily exclude its careful application to ascertain the phasing of different climate elements or proxies where the duration of the transition is longer, for example DO cooling events. However, further careful research would be required into any alternative applications to longer duration climate transitions.

Code and data availability. The CCSM4 model data are available on request from https://www.bas.ac.uk/project/sdoo/#data (last access: 22 August 2023).

The NGRIP ice core data are available from https://doi.org/10.1594/PANGAEA.935838 (last access: 22 August 2023).

The code for the ramp fitting method as well as that used to produce the figures in this manuscript are available at
https://github.com/johatt11/DO_Temporal_Phasing
(last access: 12 October 2023).

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Appendix A: Ramp Fitting Method

The deterministic component of the transition model used by Erhardt et al. (2019) to fit a series of observations x taken at times t is as follows:

$$\hat{x}(t) = \begin{cases} x_0, & \text{if } t \leq t_0 \\ x_0 + \Delta y \frac{t-t_0}{\Delta t}, & \text{if } t_0 < t < t_1 \\ x_0 + \Delta x, & \text{if } t \geq t_1 \end{cases} \tag{A1}$$

The four parameters x_0, Δx, t_0, and $\Delta t = t_1 - t_0$ are the initial value, the magnitude of the transition, the time at which the transition starts, and the duration of the transition. There are two further parameters, σ and τ, that govern the AR(1) noise which is added to the deterministic ramp in order to represent climate variability. This gives a total of six parameters. The AR1 noise process is governed by the equations:

$$x_{i+1} = \alpha_i x_i + \sigma_{eff,i}\epsilon_{i+1} \tag{A2}$$

$$\sigma_{eff,i} = \sigma\sqrt{1-\alpha_i{}^2} \tag{A3}$$

$$\alpha_i = \exp\left(-\frac{t_{i+1}-t_i}{\tau}\right), \tag{A4}$$

where ϵ_i is a normally distributed random variable with unit variance. The variance of this AR1 noise process is given by σ^2 and the autocorrelation time by τ. If the time step $t_{i+1} - t_i$ is constant then α is also constant, but we allow for the possibility of unevenly sampled data where $t_{i+1} - t_i$ varies.

Given the transition model and the transition data, Bayes' theorem can be applied to infer posterior probabilities for the model parameters:

$$p(\theta|\mathcal{D}) = \frac{p(\mathcal{D}|\theta)p(\theta)}{p(\mathcal{D})}, \tag{A5}$$

where the probability that the model exactly reproduces the data $p(\mathcal{D}|\theta)$ is named the likelihood. The prior distribution $p(\theta)$ of the model parameters encodes any a-priori knowledge on the parameters, for example required positivity. The marginal probability to observe the data $p(\mathcal{D})$ is in this context nothing but a normalization constant which in practice is not relevant. We somewhat alter the priors used by Erhardt et al. (2019) in order to ensure that we can apply the ramp fitting method to different variables across a wide range of magnitudes and units. First, we calculate initial guesses for the six parameters based on simple heuristics and shift the time-series such that our initial guess for the transition onset time t_0 lies at time $t = 0$. The

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priors used are then as follows:

$$p(t_0) = \mathcal{N}(0, 50^2) \tag{A6}$$

$$p(\Delta t) = \text{Gamma}(2.0, 0.02) \tag{A7}$$

$$p(y_0) = 1 \tag{A8}$$

$$p(\Delta y) = 1 \tag{A9}$$

$$p(\sigma) = 1 \text{ for } 0 < \sigma \leq |\Delta y| \tag{A10}$$

$$p(\tau) = \text{Gamma}(1.5, 0.05), \tag{A11}$$

with the Normal and Gamma distributions used here are defined as:

$$\mathcal{N}(\mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) \tag{A12}$$

$$\text{Gamma}(\alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} \tag{A13}$$

The prior probability for the transition onset time is a normal distribution centred around our initial guess. The use of the Gamma distribution as a prior for Δt and τ ensures that these parameters are always positive, as we require. The prior for σ also achieves this, whilst giving a uniform probability for values up to our initial guess of $|\Delta y|$. This limit is set to ensure that the noise does not dominate over the underlying transition. We use uniform distributions for y_0 and Δy to ensure that the method can be applied to any possible transition, no matter the units or magnitude.

Having a model for the underlying transition, a noise process to represent short-term climate variability, and a set of prior probabilities, the final quantity we need to produce our posterior distributions is a likelihood function. This measures the likelihood of observing the data given a particular choice of model parameters. To do so, we decompose the observed data y_i into a deterministic component $\hat{y}_i$ and a noise component x_i, $y_i = \hat{y}_i + x_i$. The likelihood function is then:

$$p(x_{i+1}|x_i, t_{i+1}, t_i, \sigma, \tau) = N\left(x_i \exp\left(-\frac{t_{i+1} - t_i}{\tau}\right), \sigma^2_{eff,i}\right) \tag{A14}$$

Together with the prior distributions, the likelihood function defines the posterior distribution $p(\theta|\mathcal{D})$ up to a constant. Since this distribution is six dimensional, it is computationally very expensive to perform any subsequent analysis. To circumvent this, an MCMC-algorithm is used to sample a representative set from $p(\theta|\mathcal{D})$. All results presented in this paper are based on the application of the computations to corresponding representative sets.

This initial formulation of the ramp fitting method is very successful when applied to transitions that do not show a large gradient either before or after the transition, as is the case for the ice core measurements for which this method was originally developed. However, some model transitions show a much more exaggerated “saw-tooth" shape, with a strongly negative gradient following the abrupt warming event. In these cases the original formulation of the method performs poorly, or sometimes totally fails.

We need to ensure that we can successfully characterise the full range of transitions within model simulations. To this end, we extend the original Erhardt method to include gradients before and after the transition with the addition of two new parameters,

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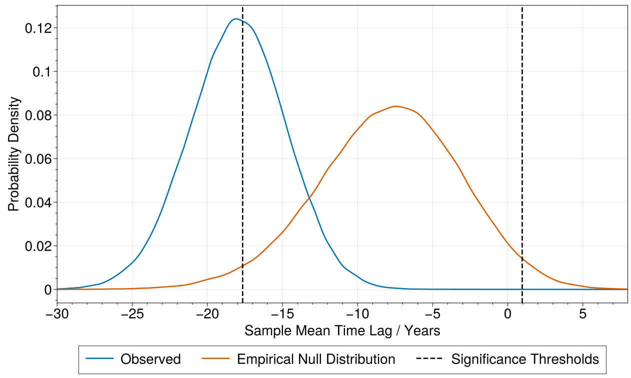

Figure B1. The observed and empirical null distributions for the sample mean time lag between precipitation and temperature in the CCSM4 model. The observed distribution here is identical to the uncorrected distribution in Fig. 4. 5% of the empirical null distribution lies outside of the significance thresholds shown as dashed lines.

taking the total to eight. These are $slope_{GS}$, the gradient in the stadial prior to the DO event, and $slope_{GIS}$, the gradient in the follow interstadial. This allows us to more accurately capture the shape of the transitions. Rather than being the initial value of the observations, y_0 is now the observed value at the start of the transition. The other parameters retain their original meanings, and the noise process is unchanged. With this extension, the deterministic component of the model is now described by the following equation:

$$\hat{y}(t) = \begin{cases} y_0 - slope_{GS}(t_0 - t), & \text{if } t \leq t_0 \\ y_0 + \Delta y \frac{t - t_0}{\Delta t}, & \text{if } t_0 < t < t_1 \\ y_0 + \Delta y + slope_{GIS}(t - t_1), & \text{if } t \geq t_1 \end{cases} \tag{A15}$$

Our initial guesses for these two new parameters are zero, and the prior probabilities, which are identical, are chosen to avoid gradients in the stadial or interstadial which are greater than those during the transition itself.

$$p(slope_{GS}) = p(slope_{GIS}) = N\left(0.0, \frac{|\Delta y|}{10\Delta t}\right) \tag{A16}$$

The prior probabilities for the other six parameters remain unchanged, as does the likelihood function.

We also test an implementation of the ramp fitting method using an alternative set of prior-probabilities similar to those employed by Capron et al. (2021). The key difference here is that the prior probabilities for the transition onset time t_0 and the transition duration dt are uniform. This implementation includes the slopes $slope_{GS}$ and $slope_{GIS}$ discussed above, and aside from the uniform priors there are no further differences.

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Appendix B: Hypothesis Test

After the bias correction, the event-averaged lead of the precipitation's transition is approximately symmetrically uncertainty-distributed around -10.0 years, with the 95% confidence interval reaching from -3.9 to -16.5 years.

In order to assess significance of this result, we test the following competing hypotheses:

- H_0: The population mean time lag for precipitation relative to temperature is equal to zero. The observed (uncorrected) precipitation lead is a spurious result induced by the method.

- H_1: The population mean time lag for precipitation relative to temperature is not equal to zero.

To test these hypothesis against each other, we design an empirical null distribution. Our null distribution will reflect the plausibility that the ramp fit assigns to a certain event-averaged (over 19 events) temporal lag $\langle \Delta t \rangle_{19}$ given that the null hypothesis is true. (The randomness associated with the individual time series involved in the computation of $\langle \Delta t \rangle_{19}$ is integrated out in our null hypothesis). We then compare the uncertainty distribution obtained from the assessment of the CCSM4 data with this null distribution. In a slight abuse of terminology, we compute a corresponding p-value as the probability that any $\langle \Delta t \rangle_{19}^{\mathrm{obs}}$ sampled from the observed uncertainty distribution is closer to the mean of the null distribution μ_0 than a second one $\langle \Delta t \rangle_{19}^{\mathrm{null}}$ sampled from the null distribution.

$$p = P\left(|\langle \Delta t \rangle_{19}^{\mathrm{obs}} - \mu_{\mathrm{null}}| < |\langle \Delta t \rangle_{19}^{\mathrm{null}} - \mu_{\mathrm{null}}| \right) = 0.078, \tag{B1}$$

To construct this distribution, we randomly sample 19 pairs of time series from the "analogous" synthetic transitions for precipitation and temperature. Application of the ramp fit to the individual pairs yields 19 uncertain time lags. From each of these 19 uncertainty distributions we sample a single value and subsequently perform the event average. 100,000-fold repetition of this procedure yields a set of time lags averaged over 19 events that reflects the randomness in the 19-fold observation of the random experiment *DO event* and the uncertainty in the timing of each transition onset.

Appendix C: Supplementary Figures

Author contributions. JS and LCS designed the study in consultation with KR. JS conducted the analysis under the guidance of KR. JS wrote the first draft of the manuscript. All authors contributed to the interpretation of the results and to the final manuscript draft.

Competing interests. The authors declare that they have no conflict of interest.

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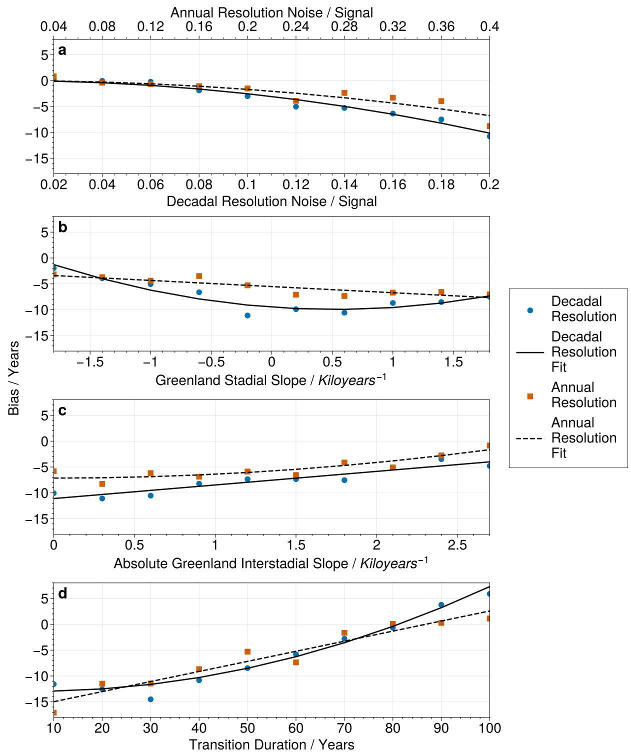

Figure C1. The dependence of the bias in the transition onset time on (a) the noise-to-signal ratio, (b) stadial (pre-transition) slope, (c) absolute interstadial (post-transition) slope, and (d) transition duration for transitions with both annual and decadal resolution, and with the other parameters held constant in all cases. Due to the “saw-tooth" shape of DO warming events, the slope during the interstadial is in fact negative in all cases, however we plot the absolute values here for clarity. Note that the scales differ between the annual and decadal data in panel (a).

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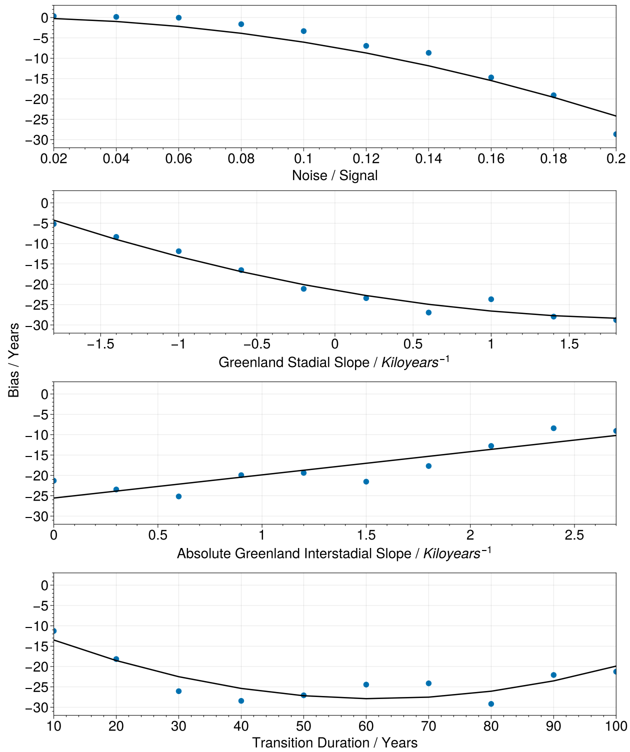

Figure C2. The dependence of the bias on four transition parameters when using uniform priors following Capron et al. (2021), for transitions with decadal resolution. For further details see Appendix A. The bias is greater than when using our standard priors (Fig. C1).

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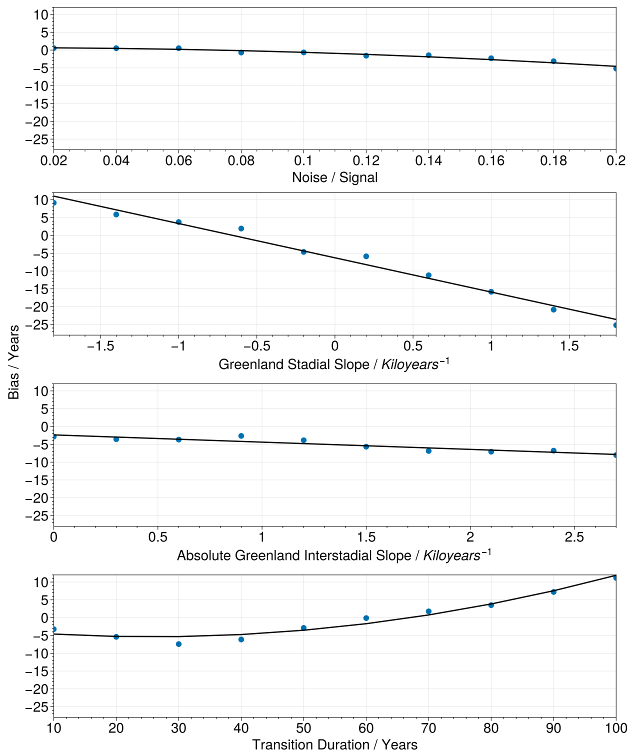

Figure C3. The dependence of the bias on four transition parameters when using the original Erhardt et al. (2019) implementation, for transitions with decadal resolution.

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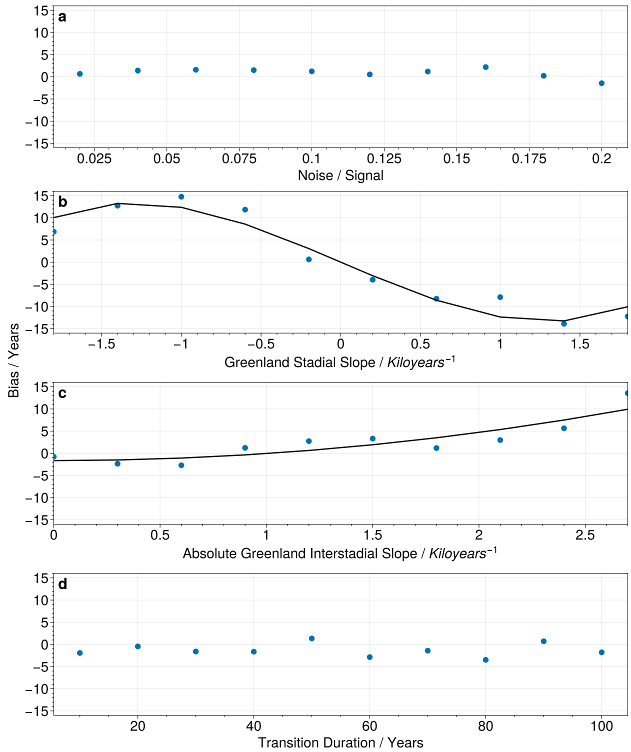

Figure C4. The dependence of the bias on four transition parameters when using a simple least-squares method instead of the Bayesian fitting method, for transitions with decadal resolution. No trend is plotted for the noise / signal ratio or for the duration, as the bias does not significantly depend on these parameters. However, there is a strong, non-linear dependence of the bias on the slopes.

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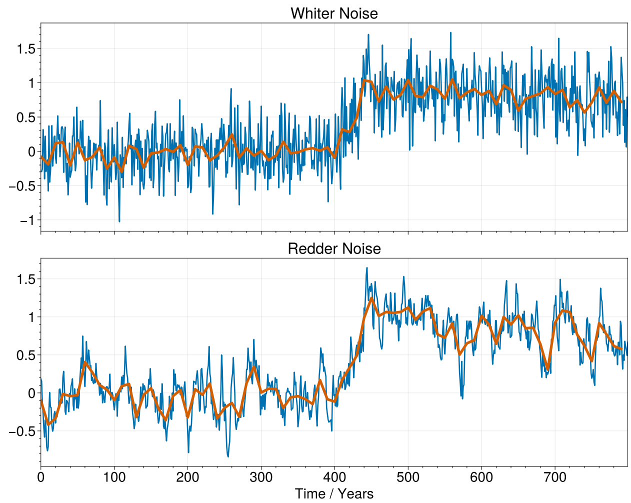

Figure C5. Examples of how we down-sample annual resolution synthetic data to decadal resolution, for the cases of both “whiter" and “redder" noise.

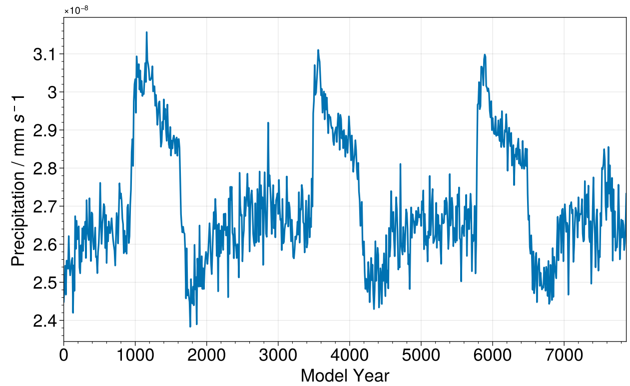

Figure C6. The time series for precipitation in the CCSM4 simulation with 200 ppm of atmospheric carbon dioxide, demonstrating the relatively higher level of noise during the cooler stadial periods, which are visible here as periods of lower precipitation.

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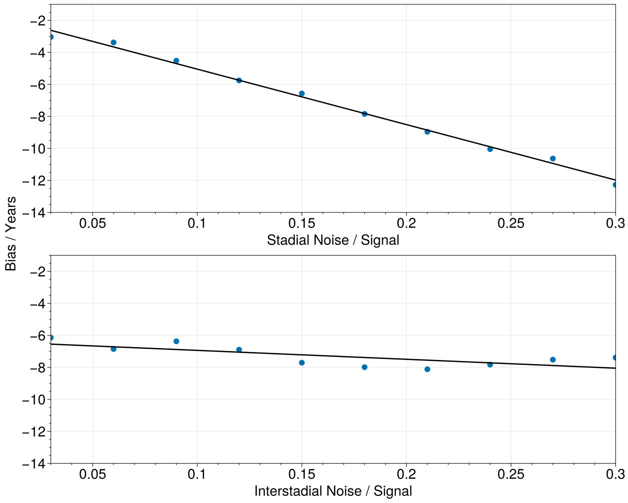

Figure C7. The dependence of the bias on noise / signal in both the preceding stadial and following interstadial, for the case of two independent noise regimes. The bias depends much more on the stadial noise / signal.

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