Climatic information archived in ice cores: impact of intermittency and diffusion on the recorded isotopic signal in Antarctica

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Abstract. The isotopic signal ($\delta^{18}O$ and δD) imprinted in ice cores from Antarctica is not solely generated by the temperature sensitivity of the isotopic composition of precipitation but also contains the signature of the intermittency of precipitation patterns as well as of post-deposition processes occurring at the surface and in the firn. This leads to a proxy signal recorded by the ice cores that may not be representative of the local climatic variations. Due to precipitation intermittency, the ice cores only record brief snapshots of the climatic conditions, resulting in aliasing of the climatic signal, and thus a large amount of noise which reduces the minimum temporal resolution at which a meaningful signal can be retrieved. The analyses are further complicated by isotopic diffusion which acts as a low pass filter that dampens any high frequency changes. Here, we use reanalysis data (ERA-Interim) combined with satellite products of accumulation to evaluate the spatial distribution of the transfer function that describes the formation of the isotopic signal across Antarctica. The minimum time scales at which the signal-to-noise ratio exceeds unity range from less than a year at the coast to a thousand years further inland. Based on solely physical processes, we were thus able to define a lower bound for the time scales at which climate variability can be reconstructed from ice core water isotopic compositions.

1 Introduction

Ice cores are key archives of past climatic conditions (Jouzel and Masson-Delmotte (2010) and references therein) as a wide range of climatic parameters are recorded in the physico-chemical composition of the ice itself and of the air bubbles trapped within. Water isotopes are commonly used as a past temperature proxy due to the sensitivity of the isotopic composition to atmospheric temperature acquired throughout the water cycle (Dansgaard, 1964; Lorius et al., 1969). Antarctic ice cores have been used to reconstruct continuous high resolution temperature time series dating back 800 000 years (Petit et al., 1999; EPICA, 2004; Kawamura et al., 2017). Ice core water isotope data have also been used to compare rapid (e.g. Dansgaard-Oeschger) events between the Arctic and Antarctica (EPICA, 2006; Markle et al., 2017) or to provide a context for the recent climate change (Stenni et al., 2017). Even though the amount of water needed to analyse water isotopes is very low (Jones et al., 2017a), inhomogeneous deposition and diffusion together with the annual layer thickness limit the temporal resolution that can be obtained from isotopes. As a result, ice cores from high accumulation areas such as Coastal Antarctica (Morgan, 1985; Masson-Delmotte et al., 2003; Küttel et al., 2012) and West Antarctica (Markle et al., 2017) could be used to achieve up

to seasonal resolution in temperature reconstructions, while ice cores from low accumulation areas such as the East Antarctic Plateau cannot be used to achieve a temporal resolution below decadal, or even multi-decadal (Petit et al., 1982; Ekaykin et al., 2002).

Due to how the signal is imprinted into the water isotopic composition in the ice of Antarctica, there are fundamental limits to the reconstructions of past temperatures based on water isotopes (Petit et al., 1982; Casado et al., 2017). For instance, before the precipitation forms near the deposition site, the isotopic composition of the atmospheric moisture keeps an imprint of all the fractionation processes that occurred since the water evaporated in the mid-latitudes (Craig and Gordon, 1965), including the subsequent condensation events that occurred while the air masses moved to high latitudes (Dansgaard, 1964). However, the local climatic signal is only archived in the snow when there is a precipitation event (Steig et al., 1994; Werner et al., 2000; Sime et al., 2009) which introduces a bias and aliasing in the recorded signal (Laepple et al., 2011; Persson et al., 2011; Sime et al., 2011; Casado et al., 2013, 2018). Even after the deposition, in central Antarctica, the accumulation not only depends on the precipitation input (Genthon et al., 2015), but is also affected by blowing snow, moving the snow layers several times before they eventually settle (Picard et al., 2019), thereby redistributing and mixing snowflakes of different isotopic composition which leads to significant stratigraphic noise in the firn isotopic composition (Fisher et al., 1985; Ekaykin et al., 2002; Münch et al., 2016). In addition, isotopic diffusion in the firn acts as a low pass filter that erases part of the climatic signal (Johnsen, 1977; Johnsen et al., 2000; Gkinis et al., 2014; Laepple et al., 2018).

Overall, although the isotopic composition of precipitation in Antarctica is relatively well correlated with local temperature, both spatially, and temporally (Landais et al., 2012; Stenni et al., 2016), the surface snow isotopic composition often does not (Touzeau et al., 2016), which suggests that it includes more than just precipitation as an input (Casado et al., 2018). In addition, comparisons of the statistical properties of the seasonal climate signal and the isotopic profiles in snow-pits have suggested that there is a large amount of noise (up to 90% of the total variance) in the input isotopic signal (Laepple et al., 2018). It is important to determine the origin of this noise as post-deposition processes (wind blowing, sublimation/condensation at the surface, metamorphism, etc.) will only affect the signal locally and be characterised by decorrelation lengths of the order of five to ten meters (Münch et al., 2017), while precipitation intermittency will have an effect over hundreds of kilometres (Agosta et al., 2019).

While there is generally a high degree of confidence in ice cores being able to yield good results as an isotopic paleothermometer at large time scales (larger than multi-decadal), at shorter time scales (seasonal to inter-annual) the climatic signal in the ice core is often difficult to read, especially at low accumulation sites. Although technical advances in analytical techniques (Jones et al., 2017b) have rendered the sampling resolution virtually unlimited, there is still a need to identify the minimum time scales at which it is possible to recover a meaningful climatic signal from the ice cores' isotopic composition. In other words, what is the theoretical lower limit for the time scale at which a meaningful climatic signal can still be reconstructed from water isotopes in ice cores? Here, we present two simple modelling approaches involving virtual ice cores to identify

the minimum resolution at which a climatic signal can be retrieved from the snow's isotopic composition in Antarctica at a predefined level of quality (signal-to-noise ratio). This approach will provide a theoretical understanding of the limitations of ice core records, particularly at low accumulation sites where the snow remains exposed for a long time before being buried. By combining approaches from Sime et al. (2011), Persson et al. (2011), and Laepple et al. (2018) we construct a forward model of virtual ice cores that includes (i) the climatic signal, (ii) precipitation intermittency, (iii) isotopic diffusion, and (iv) measurement noise. The relative contributions of each of these four contributors are then compared in a conceptual spectral model to determine the lower bounds for the time scale above which a meaningful reconstruction is possible.

2 Data and methods

2.1 Forward model for ice core records

Following Sime et al. (2011) and Laepple et al. (2018), we developed a simple forward model that uses temperature and precipitation time series to simulate virtual ice cores. For each precipitation event, the model determines the corresponding amount of snow and applies an isotopic composition that is determined by the temperature during the event. The model also accounts for diffusion and outputs are vertical depth series, that can be dated to produce an isotope time series.

Temperature is converted to isotopic composition assuming a linear relationship with a constant slope of $0.46\ ‰ \,°C^{-1}$ (Touzeau et al., 2016). We chose to use the same slope for all of Antarctica as this will allow us to distinguish between the noise generated by different distillation paths and the noise due to precipitation intermittency. While the actual value of the slope does not affect our conclusions as both the input signal and the noise scale with the same coefficient, it has a minor effect when taking into account the measurement uncertainty.

Precipitation intermittency is computed as follows: every six hours (model time step), a new layer of snow with an isotopic composition determined by the temperature (first input of the model) and a thickness determined by the amount of precipitation (second input) is added to the previous stack. This has two effects: (i) days without precipitation events will not leave any signature on the virtual ice core, and (ii) the statistical weight of the temperature on days with precipitation events is increased with the amount of precipitation. This yields an intermittent virtual core, the total depth (in meters) of which is the product of the duration of the input signal (a) and the mean accumulation rate ($m \, a^{-1}$).

For the sake of simplicity, missing noise that could be introduced when the signal is archived (stratigraphic noise, metamorphism, etc.) is parametrised as a redistribution of the signal power across all frequencies prior to diffusion, equivalent to a random reshuffling of the signal in the time domain (Münch et al., 2016). In practise, this is implemented by adding temporally independent white noise to the intermittent virtual core and renormalising the variance of the total signal (intermittent virtual core + white noise) to the variance of the original signal (intermittent virtual core only) (Laepple et al., 2018). The added white noise is controlled by two parameters: (i) the relative amount of noise compared to the input signal (0 to 100%) and (ii) the

resolution at which the noise impacts the signal (from 1 to 10 cm). The noise module in the model is used to assess the impact of additional noise sources on precipitation intermittency and isotopic diffusion.

Diffusion is applied using the classical isotopic diffusion scheme (Johnsen, 1977; Johnsen et al., 2000; Gkinis et al., 2014) of convolving the depth series with a Gaussian kernel (Johnsen et al., 2000) following Fick's law. It is characterised by a depth-dependent diffusion length (Laepple et al., 2018) that is computed for each site based on the local temperature, accumulation rate, atmospheric pressure, and the snow density. We model the snow density profiles using the Herron and Langway model (Herron and Langway, 1980) assuming a constant surface density of $350 \ \mathrm{kg \, m^{-3}}$ and setting the temperature of each site to the ERA-interim grid point value. Atmospheric pressure was kept constant at 650 mbar. The impact of both the constant atmospheric pressure and surface snow density on the diffusion length is minimal and allows for a straightforward comparison of different sites.

The virtual records (intermittent virtual core and diffused virtual core) are block-averaged to create a 1cm vertical resolution, similar to what can be achieved with manual sampling of ice cores. The virtual ice cores are perfectly dated by tagging the formation date and time to each layer. This perfect dating is used to compare the original climatic signal to the generated virtual cores, in an optimistic case. Indeed, the original climatic depth series typically shows a rather poor correlation with the generated virtual cores as their respective depth axes move quickly out of phase due to the large interannual variability in precipitation, which creates years accounting for thicker/thinner layers when the amount of precipitation is large/small. In contrast, a perfect record would only contain the climatic signal and produces the same layer thickness each year. The perfect dating enables to synchronise the virtual cores' time series on the climatic signal in order to evaluate how meaningful would a reconstruction be.

2.2 Input time series and correction

As inputs we use a 39-year (1979 - 2018) time series of 2m air temperature (T) and total precipitation (P), both from ERA-interim re-analysis providing a temporal resolution of six hours and a spatial resolution of approximately 80km (T255 spectral truncation) (Dee et al., 2011).

The ERA-interim temperature data provide good approximations of the spatial and temporal variations of the temperature observed in *in-situ* data from Antarctica (Genthon et al., 2013; Casado et al., 2018). However, compared to satellite products and *in-situ* ice core records, the ERA interim data overestimates the amounts of total precipitation by 50 to 95% (Arthern et al., 2006; Thomas et al., 2017). This is to be expected as precipitation accounts only for a fraction of accumulation in Antarctica, where up to 90% of the accumulation can be blown away by wind (Picard et al., 2019) and more than 10% of the total surface mass balance can be associated to sublimation and condensation (Genthon et al., 2017). Nevertheless, precipitation occurrence tends to correlate well with *in-situ* snow fall events in the interior of Antarctica (Libois et al., 2014), and with ice core records from Antarctica (Sime et al., 2011). This supports the use of ERA-interim precipitation since a well-captured precipitation

variability is needed to realistically model the precipitation intermittency.

However, since the diffusion length depends on the amount of accumulation, we need to compensate for the difference between precipitation and accumulation. This is achieved by applying an individual linear correction at each grid point of the reanalysis product. The correction matrix was generated using satellite data of snow accumulation (Arthern et al., 2006), that had themselves been corrected to match the accumulation obtained in ice core records (Thomas et al., 2017). For the virtual cores to have the same accumulation as actual ice cores, we use a reference accumulation rate for the years from 1960 to 2016 from a recently established database of regional Antarctic snow accumulation from ice core records over the past 1000 years (Thomas et al., 2017), selecting 71 ice cores sites with accumulations ranging from 20 to $400\,\mathrm{kg\,m^{-2}\,a^{-1}}$. The accumulation range upper limit ($400\,\mathrm{kg\,m^{-2}\,a^{-1}}$) was chosen to be representative of the low accumulation rates of the deep ice core sites (in general $<100\,\mathrm{kg\,m^{-2}\,a^{-1}}$) where the results are more sensitive to the use of an accurate accumulation rate. We use a spatial linear regression between the satellite derived accumulation (Arthern et al., 2006) for these 71 sites and the ice cores observations to calibrate the satellite data of snow accumulation on the ice core accumulation rates. Then, we interpolated the corrected satellite product to ERA-interim grid, and use the corrected satellite product as a reference for the accumulation, normalising the precipitation amount of ERA-interim to match this reference.

The impact of this correction was then assessed using the uncorrected ERA-interim amount of precipitation (See Supplementary Material S2). This affects the results locally as values of accumulation will not match reality, thereby changing the diffusion length while the modelled impact of precipitation intermittency and stratigraphic noise for a given accumulation amount remain unaffected.

2.3 Evaluating the signal-to-noise ratio in the spectral domain

In a second modelling approach, we employ a method in the frequency domain (spectral method) to evaluate the ice core signal as a combination of (i) the climatic signal, (ii) noise linked to precipitation intermittency, (iii) additional noise of unknown origin, (iv) a low pass filter due to isotopic diffusion, and (v) measurement noise. The purpose of this spectral approach is to produce time-scale dependent signal-to-noise ratios (SNR) that allow estimations of the time scales at which ice cores will be correlated with the climatic signal. We make use of the outputs of the forward model (Section 2.1) to parameterise this conceptual spectral model.

In the spectral domain, the noise added by precipitation intermittency originates from sub-sampling the climatic signal (dominated by the seasonal cycle) which in turn leads to aliasing as only the temperatures during precipitation events are recorded. Empirically, in Antarctica, precipitation events are largely random (Genthon et al., 2003; Rémy and Parrenin, 2004). During the aliasing of a signal by a random sub-sampling, the superimposed noise is white (Thomson and Robinson, 1996). The whiteness of the precipitation intermittency noise is confirmed by numerically examining the impact of precipitation intermittency using

ERA-interim data (Fig. 4). Thus, throughout this manuscript, we use this approximation and consider the added noise as white.

To evaluate how much signal is preserved after the ice core has formed, we assess the SNR in the spectral domain by the ratio of the variance of the climatic signal to the variance of the noise. In any climatic record containing signal and noise, the correlation between the reconstructed time series and the actual climatic conditions is linked to the SNR by:

$$r^2 = \frac{SNR}{1 + SNR} \tag{1}$$

By using the power spectral density (PSD) to estimate the SNR, we are able to estimate the frequency f at which the correlation between an ice core and the climatic signal reaches a defined threshold. In this study, we always set this correlation threshold as $r^2 = 0.5$, equivalent to $SNR = 1$ (Fig. 1(a)). Throughout this manuscript, we will refer to the time scale associated to the frequency for which $SNR = 1$ as τ_b (where b stands for bandpass, as analysing a single frequency is similar to applying a narrow bandpass to the record).

In general, in proxy records, averages of a given thickness are realised, either in the sampling, or by average samples. Then, the SNR corresponding to this time-averaged signal is desired. In this case, for the SNR for a given frequency, f, is expressed as:

$$SNR(f) = \frac{\int_{1/L_R}^{f} \mathcal{S}(\nu) d\nu}{\int_{1/L_R}^{f} \mathcal{N}(\nu) d\nu} \tag{2}$$

where $\mathcal{S}$ and $\mathcal{N}$ are the PSDs of the signal and the noise, respectively, and L_R is the length of the records (either in years or in metres). Graphically, this is represented in Fig. 1(a) by the ratio of the area representing the signal excess $\mathcal{A}_{signal}$ and the area representing the noise excess $\mathcal{A}_{noise}$. The associated time scale will be referred as τ_a (where a stands for averaged). If the signal is redder than the noise, the time scale τ_a where $SNR = 1$ ($r^2 = 0.5$) will be finer than τ_b.

With regard to precipitation intermittency for instance, given that we assume the noise related to aliasing of the climatic signal to be white, we can estimate the amount of noise contained at the interannual to decadal scales using ERA-interim data and apply it to lower frequency ranges such as centennial and millennial. We then compare the amount of climatic signal (provided independently) to the constant white noise due to precipitation intermittency and estimate the frequency at which an ice core will present a correlation of $r^2 = 0.5$. In addition to the noise induced by precipitation intermittency, several other sources of noise can influence the signal recorded by ice cores such as stratigraphic noise (Fisher et al., 1985). All types of noise can be combined in this method to the collective term of *archiving noise* (Fig. 1(a)).

Adding the impact of diffusion results in a convolution of both the signal and the archiving noise with the diffusion transfer function (Fig. 1(b)), and thus doesn't directly affect the SNR also reflected by the fact that diffusion can be inverted ("back diffusion") (Münch and Laepple, 2018). However, in practice, additional measurement noise is added to the signal after diffusion has taken place which limits the potential of back-diffusion. We include this effect in the estimation of the frequency at which
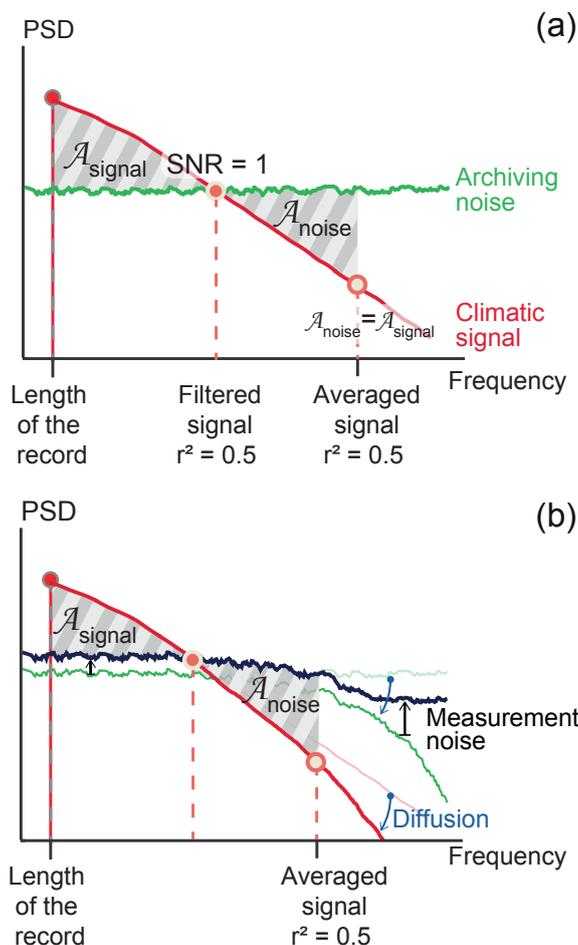
Figure 1. Schematic of the signal to noise ratio (SNR) estimate using the power spectral density (PSD): (a) idealised PSD of the climatic signal (red) and of the archiving noise (green) which consists of noise induced by precipitation intermittency and stratigraphic noise; (b) impact of diffusion on the same PSDs (light colours: before diffusion, dark colours: after diffusion) and of measurement noise (black).

a meaningful signal can be retrieved by adding a measurement noise offset to the initial archiving noise after diffusion has taken place (Fig 1 (b)). This additional noise reduces the area of excess signal and increases the area of excess noise, thereby reducing the frequency at which the correlation between an ice core record and the climatic signal reaches $r^2 = 0.5$.

3 Results

3.1 Illustrating the methodological approach

In order to illustrate the methodological approach and the results of the forward model, we chose the location of the drilling site of Epica Drowning Maud Land (EDML) near Kohnen station for which a large number of snow pits are available (Münch

et al., 2016; Laepple et al., 2018).
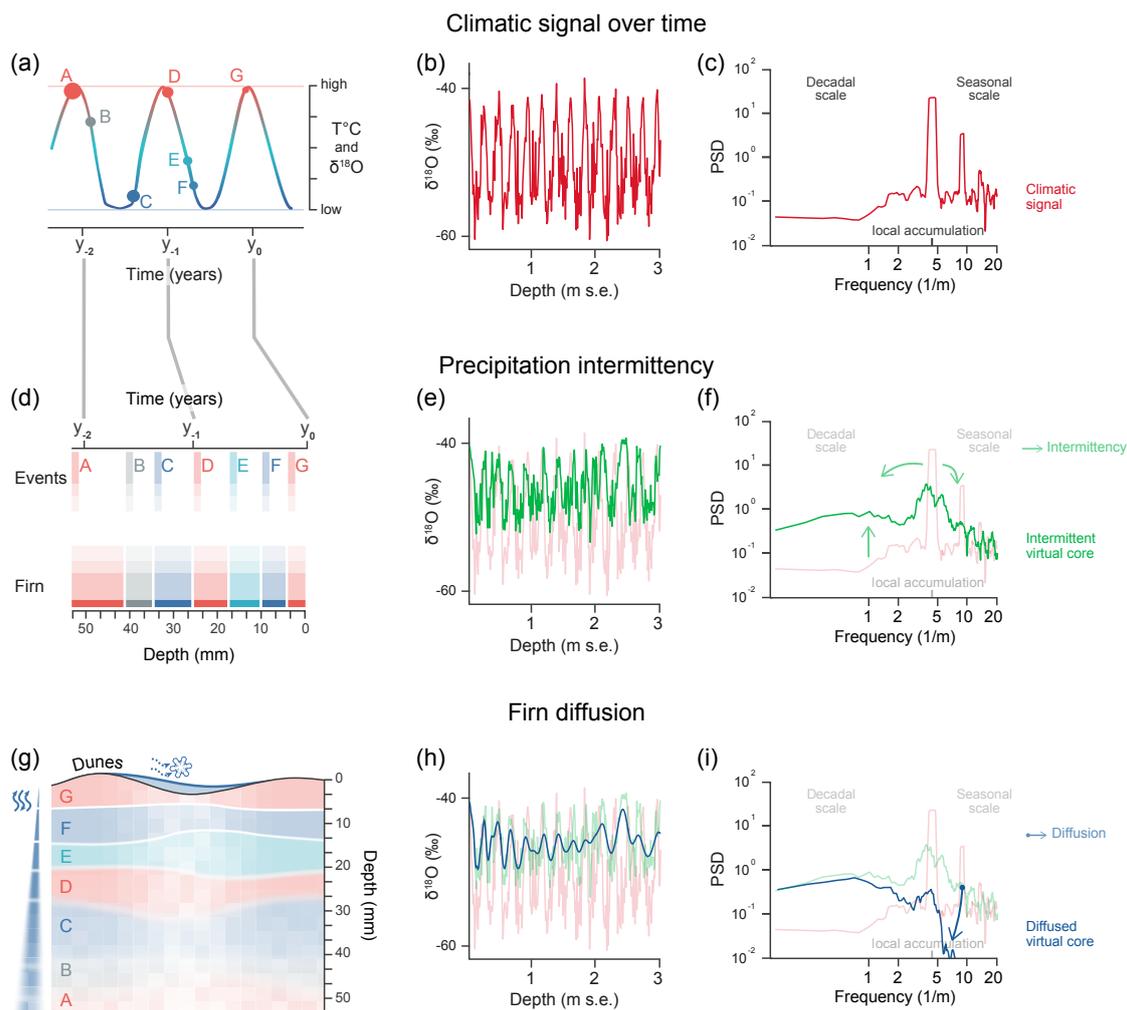
Figure 2. Description of the archival processes included in the forward model that lead to a loss of signal in the snow isotopic composition. Examples are for EDML: (a) idealised temperature time series with rare precipitation events (capital letters A to G); (b) climatic virtual core: actual temperature time series converted to an isotopic profile for the case of constant daily precipitation; (c) power spectral density of the climatic virtual core in (b); (d) schematic illustrating the impact of precipitation intermittency on the layering of the isotopic profiles; (e) intermittent virtual core: isotopic composition after precipitation intermittency has affected the signal; (f) power spectral density of the intermittent virtual core in (e); (g) schematic illustrating the impact of snow redistribution and isotopic diffusion on the snow layering; (h) diffused virtual core: isotopic composition after precipitation intermittency and diffusion have impacted the signal, (i) power spectral density of the diffused virtual core in (h).

A first virtual core is generated for the pure climate signal (Fig. 2 (b)) which corresponds to a perfect record as each day is archived and no information is lost. As for most sites in Central Antarctica, the climatic signal at EDML is dominated by the seasonal cycle which leads to a large peak in the PSD at the frequency that corresponds to the local accumulation and a smaller peak corresponding to the second harmonic (Fig. 2 (c)).

Since water isotopes only create an archive of the temperature conditions during precipitation events, many days will not have been recorded. In addition, large precipitation events will lead to thicker layers of snow which in turn have a stronger statistical impact on the overall signal recorded in the ice core (Fig. 2 (d)). These effects are included in the precipitation intermittency virtual core (Fig. 2 (e)) for which the amount of variance is reduced as there is a systematic warm bias in winter that leads to an under-representation of the coldest conditions (Casado et al., 2018). As a result, the difference between the precipitation-weighted temperature and the actual temperature is larger in winter than in summer (Fig. A1). Throughout Antarctica, the amount of lost variance is positively correlated with the difference between the mean of the intermittent virtual core and the climatic core ($r^2 = 0.34$, n = 12128), which suggests that the amount of lost variance is due to the under-sampling of the colder winter conditions (Fig. A1). Nevertheless, the amount of variance preserved in the intermittent virtual core ranges from 30 to 100% of the amount of variance observed in the climatic signal. However, precipitation intermittency redistributes the very strong seasonal signal across frequency (Fig. 2 (f)). Analysing the depth series, we observe no correlation between the intermittent and the climatic virtual cores due to the seasonal cycles being out of phase due to interannual variations in the amount of precipitation. Analysing the time series, if each layer was perfectly dated we would obtain a correlation of $r = 0.85$.

Accounting for diffusion reduces the variance (Fig. 2(h)) mainly due to the damping of high frequency variations. At EDML, the diffusion low-pass filter starts to have a strong effect at frequencies corresponding to length scales smaller than the local accumulation rate, i.e. at the interannual scale. Under the perfect dating assumption, the diffused core is correlated to the climatic signal with $r = 0.22$, mainly due to the most recently deposited near-surface layers that have not been diffused yet. This is visible in the PSD of the diffused core as a peak remaining near the frequency that corresponds to the annual accumulation.

3.2 Outputs of the forward model across Antarctica

By producing similar virtual cores for each grid point of the ERA-interim reanalysis product, we can illustrate the impact of the archival processes on the signal by comparing the correlation of the virtual cores of each site with the climatic signal under a perfect dating assumption (Fig. 3). Precipitation intermittency alone (Fig. 3(a)) only slightly reduces the correlation of the full time series (mean correlation across Antarctica: $r = 0.88$). As the seasonal cycle clearly dominates the signal by roughly two orders of magnitude (Fig. 2 (c)), the correlation is reduced at a large number of interior sites when applying a two-year running mean filter (henceforth referred to as interannual low-pass filter), and analysing the aliasing effect due to precipitation intermittency at interannual and decadal scales (Fig. 3(c)).
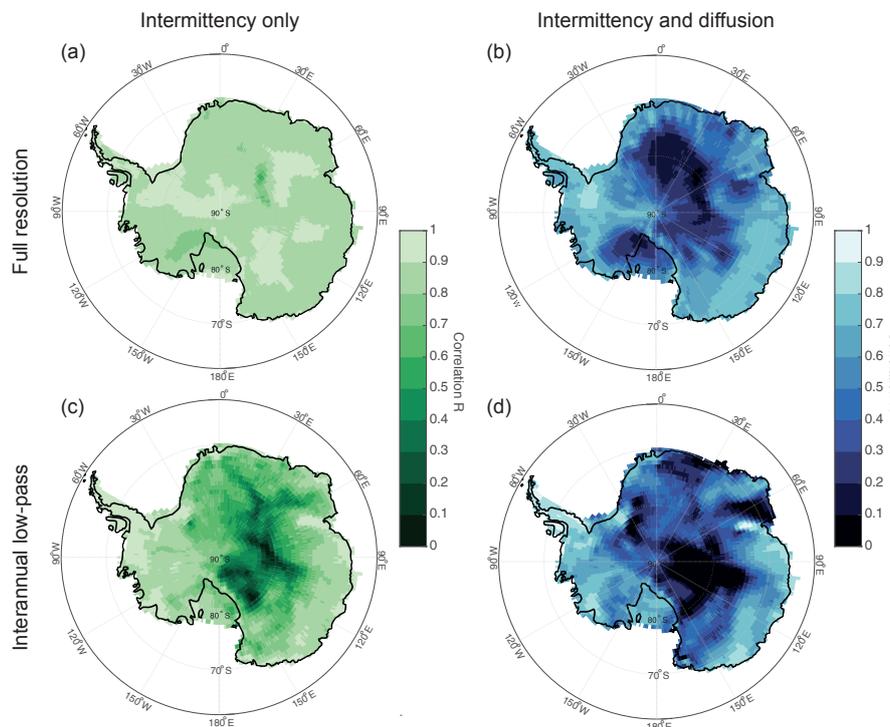
Figure 3. Maps showing the correlation between the climatic signal and perfectly dated virtual cores: (a) and (c) precipitation intermittency only (green); (b) and (d) precipitation intermittency and diffusion (blue). The top panels (a) and (b) present the correlation using the complete time series, while the bottom panels (c) and (d) show the correlation for the time series that has been smoothed with the two-year running mean.

After diffusion, the correlation between the virtual core and the climatic signal drops on the East Antarctic Plateau, Marie Byrd Land, and the Ross Ice Shelf (Fig. 3(b)). Part of the remaining correlation is due to remnants of the seasonal cycle that have been preserved (mean correlation across Antarctica: $r = 0.50$). By filtering out any signal below the interannual scale, large areas exhibit a drop in correlation, particularly in the interior (Fig. 3 (c) and (d)). In areas exhibiting a drop of correlaiton, while the forward model shows significant correlation with the climate signal at sub-annual resolution (up to $r = 0.9$), there is no power of reconstruction because artificial signals at interannual scales, mostly due to precipitation intermittency, would make it impossible to retrieve any signal.

3.3 Impact of intermittency at long time scales

In order to investigate the effect on time-scales relevant for ice-core studies, we extend our results up to centennial and millennial time-scales and focus first on the impact of precipitation intermittency. As the time series input we used (ERA-interim) only covers 40 years, in order to extend the study to larger time scales, we make use (i) of the approximation that the noise generated by precipitation intermittency is white, and (ii) make assumptions on the spectrum of the climatic signal. (see section

2.3).

We estimate the noise level added by precipitation intermittency from the difference between the power spectral densities of the intermittent virtual core and the climatic signal virtual core over the interannual and decadal scales (more specifically, for frequencies below 3/2 a^{-1}, hatched area in Fig. 4). As the noise is white, we generalise this level for longer time scales (see the dashed line in Fig. 4). For instance, in the case of EDML, using ERA-interim as an input, we obtain a white noise level of 0.59 ‰^{2} m using the difference between the intermittent virtual core (green curve) and the climatic virtual core (red curve). For the period covered by ERA-interim, the signal strength never reaches the noise level at EDML, except for the frequency associated with the seasonal cycle (Fig 4). The SNR based correlation between the intermittent virtual core and the climatic signal at interannual scales will be below $r^2 = 0.5$, while the time series correlation obtained by comparing the virtual cores at EDML is $r^2 = 0.15$.
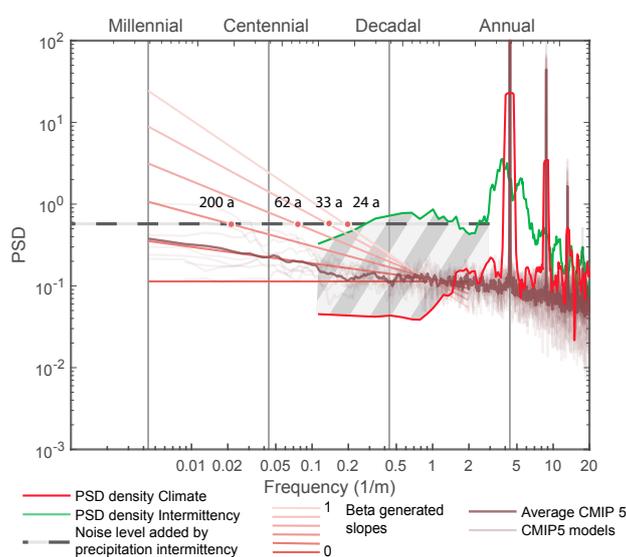
Figure 4. Comparison of the amount of noise generated by precipitation intermittency and different hypothesis for the climatic signal: PSD generated by the forward model for the climatic signal (red) and the precipitation intermittency (green) virtual cores; area where the noise level added by precipitation intermittency is calculated (hatched zone) and noise level threshold (hatched line); and several hypothesis for the climatic signal input over a 1000 years. The time scales at which a meaningful climatic signal can be found (τ_b, see Section 2.3) are given as the intersection of the noise level and the climatic signal inputs.

To obtain an input climatic signal for longer time scales, we use spectra of 1000 years forced simulations from the CMIP 5 model ensemble. We first produced the PSD of the temperature data for the last 1000 years for each grid point of 8 of the CMIP 5 models (BCC-CSM1-1, CCSM4, CSIRO-Mk3L-1-2, FGOALS-gl, GISS-E2-R, IPSL-CM5A-LR, MIROC-ESM, MRI-CGCM3). The temperature PSD were then resampled to the ERA-interim grid and converted to $\delta^{18}O$ variance (see Sec-

tion 2.1). The results, displayed in brown in Fig. 4, show that while some individual models predict a sufficiently strong signal that can be distinguished from the noise created by precipitation intermittency, the average SNR remains below 1.

We consider alternative assumptions to GCM regarding the climatic variability at large time scales, which might more accurately represent the amount of variance observed in ice cores. One of the simplest assumption to explain the observed variance is to assume a power law relationship for the PSD of the signal ($\mathcal{S}(f)$) (Lovejoy and Schertzer, 2013):

$$\mathcal{S}(f) \propto f^{-\beta} \tag{3}$$

where β is the scaling exponent. For the CMIP 5 model ensemble, the scaling exponent obtained at EDML was $\beta = 0.2$, while EDML ice core records for the last 1000 years indicate a scaling exponent of around $\beta = 0.6$ after correcting for local non-climate variability (Münch and Laepple, 2018). Here, we investigate β between 0 and 1 to cover the range of reasonable scaling behaviours of temperature.

At EDML, the time scale τ_b for which $SNR = 1$ varies from more than 1000 years when $\beta = 0$ or 0.2, to 24 years when $\beta = 1$ (See Table 1). In this case, it means that analysing the amount of signal at a specific frequency (for instance, as is commonly done to evaluate the solar cycles), an ice core drilled at a site with climatic conditions characterised with a value of β, a SNR of 1 would be reached for the resolution τ_b (see Table 1) in the best case scenario as no other effects than precipitation intermittency are considered.

Table 1. Time scales τ_b for which $SNR = 1$ for a specific frequency (band-pass filtering) after precipitation intermittency at EDML.

β	0	0.2	0.4	0.6	0.8	1
τ_b (a)	/	/	200	62	33	24

Usually, ice cores are averaged to a lower resolution (either by measuring long bars of ice as a block, or by averaging after the measurement is done at finer scale). We compute the time scales at which signal will be preserved after the intermittency, taking into account the impact of averaging for a time series of 1000 years (Table 2).

Table 2. Time scales τ_a for which $SNR = 1$ for averaged samples for precipitation intermittency for at EDML.

β	0	0.2	0.4	0.6	0.8	1
τ_a (a)	/	/	91	17	7.4	3.9
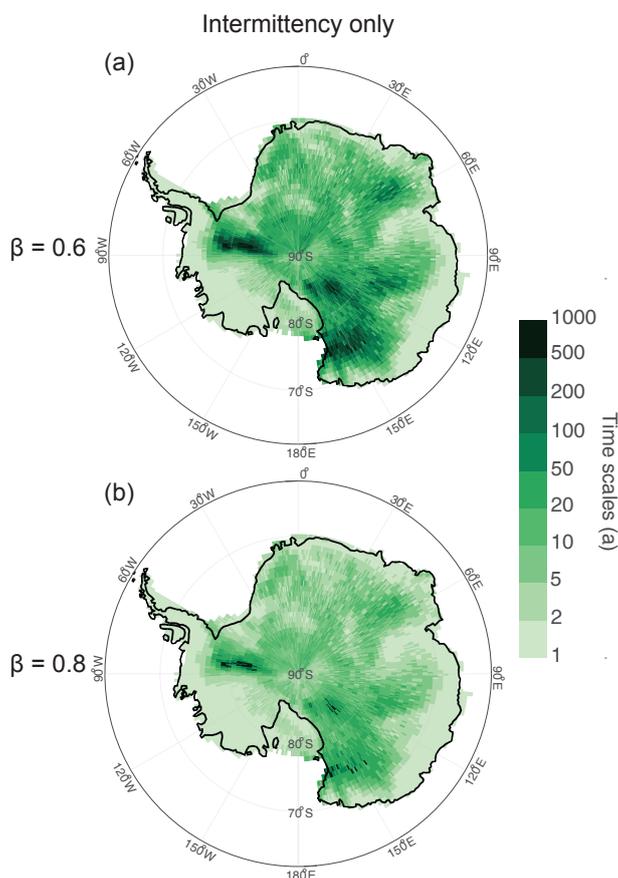
Figure 5. Maps of the time scales τ_a at which an integrated SNR of 1 is reached for the case of precipitation intermittency only and averaging the core to a certain time scale for (a) $\beta = 0.6$, and (b) $\beta = 0.8$.

The time scales at which signal is preserved after precipitation intermittency has impacted the signal recorded in ice cores are presented in Figure 5. For a value of $\beta = 0.6$, as estimated from isotope data of the last millennium (Münch and Laepple, 2018), the time scales range from one year in coastal areas to 1000 years for special areas of the interior (e.g. Ellsworth Land and Victoria Land). For a value of $\beta = 0.8$, i.e. assuming more low frequency climate variability, the time scales are globally reduced. In both cases, the spatial pattern cannot be entirely explained by the amount of accumulation: while the low accumulation areas of the East Antarctic Plateau have large values of times scales at which the integrated $SNR = 1$, τ_a (from 10 to 500 years), the largest τ_a are found for around Ellsworth Land where the amount of accumulation is much larger (see Supplementary Material).

3.4 Impact of diffusion

Isotopic diffusion continues to affect the isotopic signal after snow deposition has occurred. As a result, the impact of isotopic diffusion increases with depth in the firn column. To illustrate the impact of diffusion and compare it to the impact of precipitation intermittency, we present the results for the diffusion length values at a depth equivalent to the lock-in depth, for simplicity, here assumed to be 100m.
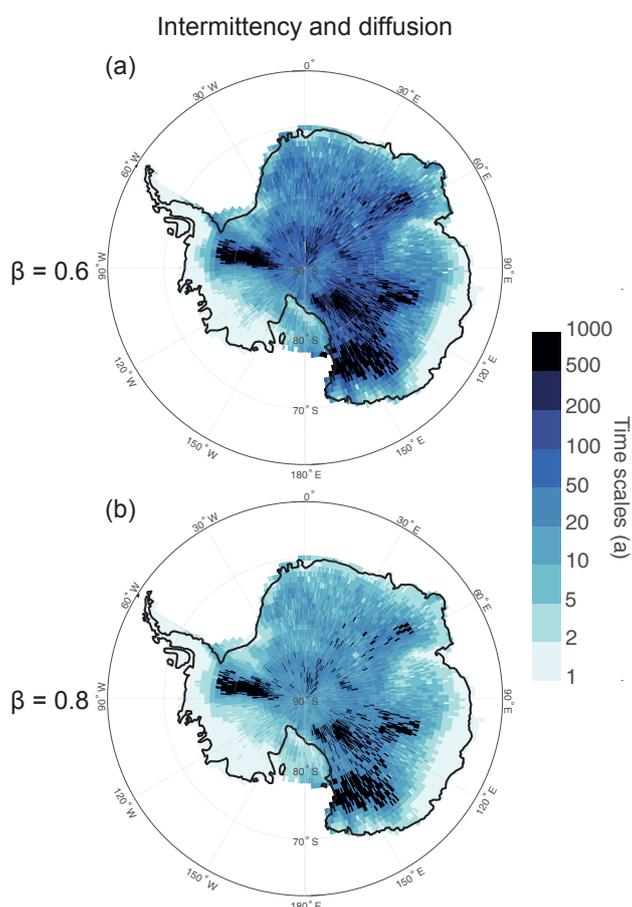
Figure 6. Maps of the time scales τ_a at which an integrated SNR of 1 is reached for the case of averages after precipitation intermittency, diffusion and measurement error (0.1 ‰^{2}) have affected the signal... for the case of an climatic input signal with (a) $\beta = 0.6$, and (b) $\beta = 0.8$.

As for precipitation intermittency, we account for diffusion using artificial signals characterised by scaling with β varying from 0 to 1 which we compare to a noise level. Here, we apply the diffusion transfer function to both the input signal, and the white noise generated by precipitation intermittency. The impact of additional noise affecting the signal after diffusion, such

Table 3. Time scales τ_a for which $SNR = 1$ for averaged samples after precipitation intermittency, diffusion, and measurement noise at EDML.

β	0	0.2	0.4	0.6	0.8	1
τ (a)	/	/	143	23	9.2	4.6

as measurement noise, will limit the ability to back-diffuse an ice core signal. We account for this impact by comparing the diffused signals to a measurement noise level. Weassume a measurement noise level of 0.1 ‰^{2}. As before, we calculate the time scales for which the integrated $SNR = 1$, with the noise including both a diffused white noise linked to precipitation intermittency, and a pure white noise linked to measurements (Fig 6).

Diffusion and the additional measurement noise mainly affect areas with low accumulation (where diffusion is more important), which leads to an increase in the time scales at which a signal can be retrieved mainly in the interior. At EDML, the values are larger, especially for smaller values of β (Table 3).

3.5 Comparison with snow pits *in-situ* measurements

In the spectral domain, we can compare the PSDs of the simulated isotopic profiles that include precipitation intermittency and diffusion to the PSDs obtained for snow pits from sites all across Antarctica that exhibit a wide range of accumulation and temperature (Fig. 7). As illustrated by Laepple et al. (2018), observations from snow pits lack any clear periodicity, particularly at the frequency associated to the seasonal cycle. In contrast, our model maintains some additional power at the frequency associated to the local accumulation $(1a^{-1})$ even when accounting for precipitation intermittency and diffusion (see the blue vs black curve in Fig. 7). In addition, the model output shows reduced variance compared to the observations at the lowest frequencies (between $0.1\mathrm{m}^{-1}$ and the frequency associated to the accumulation).

Laepple et al. (2018) have shown that in order to generate accurate PSDs of snow pits in Antarctica, up to 90% of the total variance of the input signal before diffusion needs to be white noise. The patterns observed here correspond to a lack of noise compared to their estimates, which is expected as long as we do not account for stratigraphic noise (see Discussion). We can produce modelled profiles that better reproduce the PSD of observations for the three sites described here by converting more of the signal to white noise. In order to obtain the best fitting PSDs, at EDML, the added noise accounts for 60% of the total variance and affects the virtual core at a resolution of 5 cm. At Dome C, the parametrisation of added noise that yields the best fit is 80% of the total signal and a resolution of 2 cm. At WAIS, corresponding noise level is 80% of the total signal at a resolution of 10 cm.
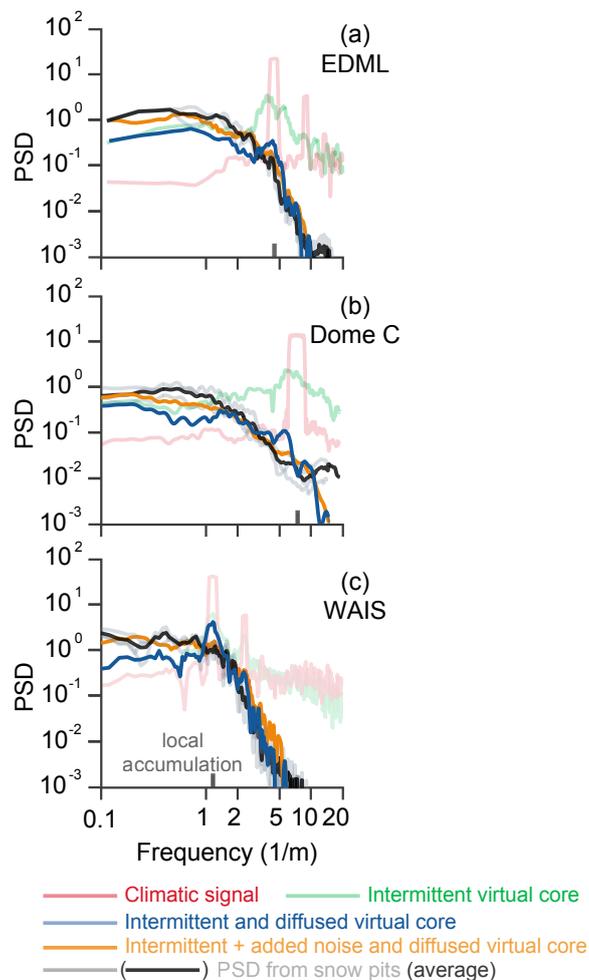
Figure 7. Power spectral density of the virtual ice cores compared and of isotopes profiles from snow pits for (a) EDML, (b) Dome C, and (c) WAIS: climatic signal (light red), intermittent virtual core (light green), intermittent and diffused virtual core (light blue), intermittent + added noise and diffused virtual core (orange), snow pits from the sites (individual: grey, average: black).

4 Discussion

4.1 Impact of the results on the interpretation of ice core records

Ice core isotopic composition is traditionally used as a temperature proxy. For sites with very low accumulation such as Vostok, Dome C, or Dome F where the oldest ice core records have been obtained (Petit et al., 1999; EPICA, 2004; Kawamura et al., 2017), temperature records are typically retrieved at centennial or decadal scales (EPICA, 2006). For instance, in the Dome C ice core, the 55cm sampling rate and the varying accumulation yielded a temporal resolution 15 to 30 years during the last Glacial Period. Here, we suggest that the temporal resolution of the time series obtained from ice core records should not be

just based on the sampling rate of the ice core. Our results cast doubts on the amount of climate signal that can be retrieved from very high resolution records (bellow annual), even if the climatic signal is back-diffused. The unexpectedly large impact of precipitation intermittency in the form of white noise is masking much of the high frequency variability. In agreement with previous studies, our results suggest that signal at scales below decadal to multi-decadal cannot be recovered from ice cores collected on the East Antarctic Plateau (Petit et al., 1982; Ekaykin et al., 2002).

As an visual representation to our findings, a simplified calculation of the impact of precipitation intermittency and diffusion on a long term temperature time series (TRACE 21k) (Liu et al., 2009) for Dome C is presented in Fig. 8 (see Appendix B). Precipitation intermittency adds a large amount of non-climatic noise, clearly visible at the resolution applied to extract data from the Dome C ice core (Fig. 8(a), light green curve). While the standard deviation for the intermittent virtual core for the last 1000 years is $\sigma_{1\,ka} = 2.6\,K$, the climatic signal has a standard deviation of $\sigma_{1\,ka} = 0.64\,K$. The intermittent virtual core and the climatic signal are uncorrelated during stadial periods (Holocene and Last Glacial Maximum), and only show a notable correlation during the climate transition after averaging to scales larger than 60 years ($r^2 \geq 0.5$). This is expected as the scaling of Trace 21k was only $\beta = 0.27$, much smaller than the values expected from ice core records (around 0.6) (Münch and Laepple, 2018), and thus associated with a poor SNR according to our results.

The diffused virtual core sampled at the ice core resolution has a variance ($\sigma_{1\,ka} = 1.5\,K$) that is lower than for the intermittent virtual core, but still larger than the climatic signal (Fig. 8(b)). Although we only included the present level of precipitation

Table 4. Time scales τ_a at which signal can be retrieved (SNR = 1 for the average time series) for the main Antarctic ice core sites including the impact of precipitation intermittency, diffusion and measurements noise. Note that due to the Shannon-Nyquist theorem, the actual resolution of the record must be $\tau_a/2$ in order to obtain signal at the frequency $1/\tau_a$.

Ice core sites	Scaling as GCM $\beta \approx 0.2$	Prescribed scalings $\beta = 0.6$	$\beta = 0.8$
Dome C	> 1 000	27.8	10
EDML	> 1 000	23	9.2
Vostok	> 1 000	30	11
Dome F	> 1 000	12	4.6
Dome A	> 1 000	29	11
South Pole	> 1 000	15	6.5
RICE	2.3	1.1	0.81
TALOS	> 1 000	100	27
WAIS	9.0	1.8	1.3
Law Dome	< 0.50	0.66	0.50
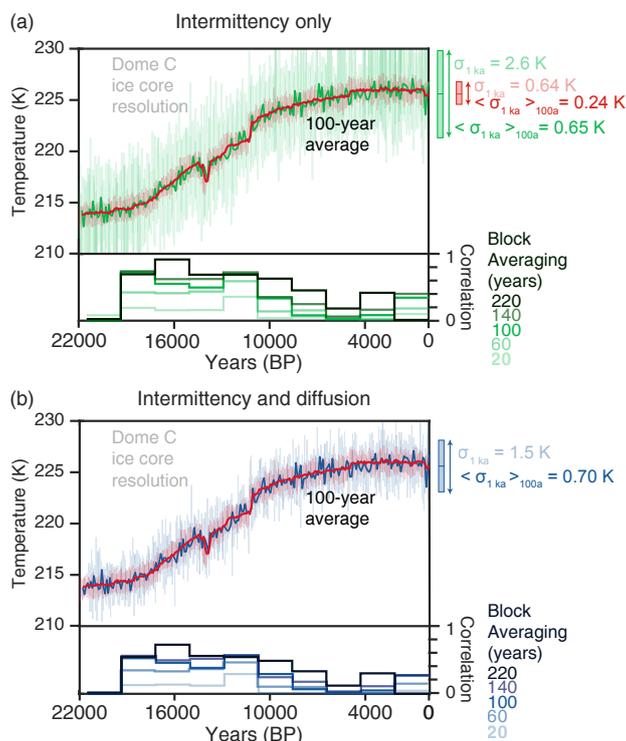
Figure 8. Application of the forward model to a temperature time series of the last deglaciation obtained from Trace 21k at Dome C. The pure climatic signal has been resampled at a fixed temporal resolution to match the sampling rate of the top of the ice core (5.8a, light red), and also at 100a resolution (dark red). (a) intermittent virtual core (light green: ice core resolution, dark green: 100a average) and block-correlation between the intermittent virtual core and the climatic signal for different block-averaging. (b) intermittent and diffused virtual core (light blue: ice core resolution, dark blue: 100 a average) and running-correlation between the intermittent and diffused virtual core and the climatic signal for different block-averaging.

intermittency and isotopic diffusion, this value is of the same order of magnitude as the one obtained for the actual temperature reconstruction from the Dome C ice core ($\sigma_{1\,ka} = 0.94\,K$) (EPICA, 2004).

Overall, our results are in agreement with the call for caution made by Sime et al. (2009) when interpretating isotopic composition fluctuations in individual ice core records. We have shown here that across Antarctica, precipitation intermittency adds a significant noise component to the water isotopes signal in ice cores due to the aliasing of the seasonal cycle (Persson et al., 2011). Using spectral methods, we could determine the lower limit for the time scales at which the ice core signal is correlated with the climatic signal. Isotopic composition profiles from snow pits on the East Antarctic Plateau exhibit a systematic visual similarity apparent to cycles with a period of roughly 20 cm (Casado et al., 2018) mostly due to diffusion of a signal dominated by white noise (Laepple et al., 2018). Our results indicated that a large part of the noise that needs to be added to the climatic signal is due to precipitation intermittency (63% on average across all Antarctica).

4.2 Additional impact of stratigraphic noise

All three snow pit sites that we compared to our model outputs pointed toward some missing noise that needed to be added prior to diffusion. Stratigraphic noise could be a likely candidate for this missing noise (Fisher et al., 1985), which is mostly white (Münch and Laepple, 2018) and results from a range of processes that affect the snow while it remains at the surface such wind blowing (Groot Zwaaftink et al., 2013), sublimation and condensation (Casado et al., 2016; Ritter et al., 2016; Genthon et al., 2017), and surface metamorphism (Picard et al., 2012; Casado et al., 2018). Stratigraphic noise would further reduce the correlation between the climatic signal and the ice cores. In particular, it decreases the amount of variance associated to the seasonal cycle.

The amount of additional noise needed for the model outputs to match the PSDs of the observations matches the amount of stratigraphic noise obtained independantly in Antarctica. Using the correlation between two trenches at EDML, Münch et al. (2017) estimated that the stratigraphic noise for the site of EDML accounts for 50% of the total signal, which is of the same order of magnitude as our estimate of the additional noise of 60% (Fig. 7). No corresponding estimate exists for Dome C. We do know, however, that the amount of snow accumulating at Dome C corresponds to only 10% of the amount of snow being deposited (i.e., about 90% is blown by wind several times before settling definitively) (Picard et al., 2019), which would suggest a similar amount of stratigraphic noise as our estimate of 80 % of the total variance.

For a level of stratigraphic noise of 60% of the total variance of the climatic signal (as observed at EDML, (Münch and Laepple, 2018)), we obtain, on average a doubling of the value of the time scales at which a meaningful signal can be retrieved, τ_a (see Fig. 9). We expect stratigraphic noise to have a different spatial patterns than the noise associated with precipitation intermittency, as both processes involve different physical mechanisms: wind blowing, sublimation and condensation, metamorphism in stratigraphic noise versus in precipitation formation in precipitation intermittency. An additional quantitative evaluation of the amount of stratigraphic noise with respect to the total variance of isotopic records would be necessary to be able to parameterise stratigraphic noise in our forward model.

While both stratigraphic noise and precipitation intermittency add white noise to the climatic signal, it is important to distinguish as spatial and temporal properties of the white noise in each case. Stratigraphic noise from two locations separated by only a few meters will be essentially uncorrelated (Münch et al., 2016), while precipitation intermittency can exhibit a correlation across areas as large as 100 x 100 km (Agosta et al., 2019). As a result, any attempt to increase the SNR by averaging several ice cores will need to take into account the different decorrelation lengths of both these noise sources (Münch and Laepple, 2018). On the one hand, to reduce the impact of stratigraphic noise, averaging two or more ice cores collected 10 m apart from a single site would be sufficient. On the other hand, to reduce the impact of precipitation intermittency, it will be necessary to collect the two ice cores from further appart which may introduce a bias as the two further apart sites may have
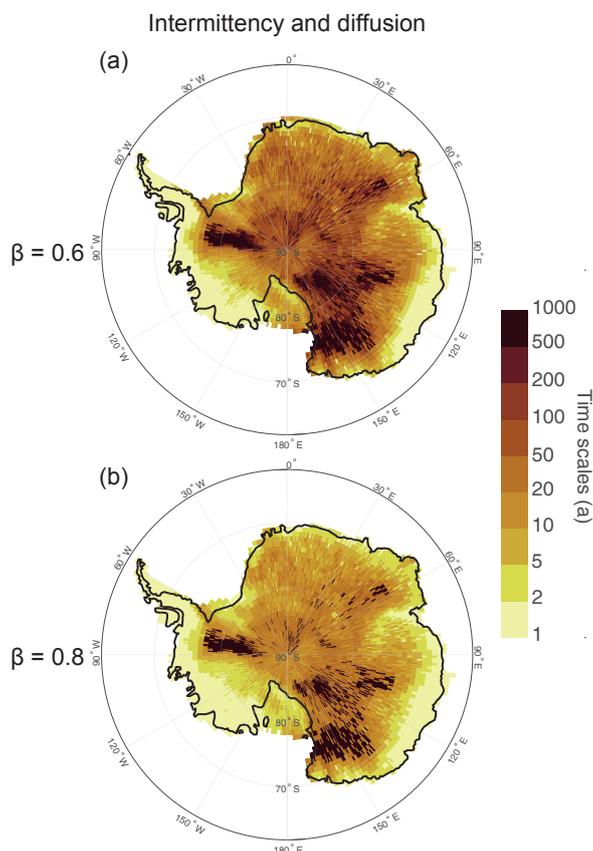
Figure 9. Maps of the time scales, τ_a at which an integrated SNR of 1 is reached for averaged data including precipitation intermittency, a stratigraphic noise corresponding to 60% of the climatic signal, diffusion, and an additional measurement noise level of 0.1 ‰. The climatic input signal was generated using (a) $\beta = 0.6$, and (b) $beta = 0.8$.

slightly different local temperature variations. Further biases may also be introduced by dating uncertainties.

As a result, if one was able to make a large number of cores at a single site, the limit at which signal would be retrievable would be the one without considering the impact of stratigraphic noise, as presented in Fig. 6. In the typical case of having just one core for a given site, the minimum time scale at which a meaningful signal can be retrieved is the one that includes stratigraphic noise (Fig. 9).

4.3 Limits of the present methodological approach

The first approximation on which we are basing the calculation of the time scales at which signal can be retrieved is the white noise approximation, which implies that the amount of white noise generated by both precipitation intermittency and stratigraphic noise has remained constant through time. This approximation may not hold as precipitation patterns and amounts may

have been different in the past, and thus change our postulated time scale limits. General Climate Models (GCM) can provide estimations of the changes in precipitation intermittency in the past, especially if they are linked to changes in the atmospheric circulation.

In order to evaluate the time scales at which the climatic signal is recorded by the isotopic composition of the ice cores, we need to make certain assumptions about the spectrum of the climatic signal. Using a GCM to estimate the spectrum of the climatic signal yields >1000a for the time scale at which climatic signal is archived in ice cores in Central Antarctica. These simulation results stand in contrast to *in-situ* observations (Münch and Laepple, 2018), which suggest that the true regional climatic variability may be higher than predicted by GCMs (Laepple and Huybers, 2014), and thus leads to more optimistic results.

This study provided only a lower boundary for time scales at which a signal can be retrieved while taking into account what we believe to be the major contributors. However, there are several additional processes that affect the isotopic signal. First, dating affects the quality of the retrieved signal. We used a perfect dating by tagging each layer of snow with a date. For a real ice core, the uncertainty associated with the dating due to variable accumulation amounts in between tie points also impacts the signal.

To generate the maps of time scales at which $SNR = 1$, we assumed isotopic diffusion to be constant, using a value that corresponds to diffusion at a depth of $100\,\mathrm{m}$, similar to the lock-in depth. In reality, the amount of diffusion may have varied in the past and will vary with depth from firn diffusion (Johnsen, 1977; Johnsen et al., 2000; Laepple et al., 2018), layer thinning to ice diffusion (Pol et al., 2014). This can easily be included in our approach through the use of a more complete transfer function of diffusion which requires prior knowledge of the variations of diffusion processes.

5   Conclusions

We provided a forward modelling approach to estimate the lower time scale at which meaningful signals can be extracted from ice cores, taking into account potential effects from (i) precipitation intermittency, (ii) diffusion, and (iii) measurement noise. This was achieved by estimating the spectral properties of these three processes using ERA-interim time series of temperature and precipitation.

Our results underline that the ability to reconstruct past climate conditions from ice cores depends not only on the noise level imposed by precipitation intermittency and stratigraphic noise, but also on the strength of the input signal. As a result, a particularly strong signal, such as the deglaciation, will be imprinted in the ice cores at much higher resolution than the limited Holocene temperature variations in Antarctica. Potential variations in the noise levels during past climatic conditions will also

strongly affect the results.

The systematic analysis of the various processes that affect how climatic signals are stored is important for high-resolution climate reconstructions. We propose that the use of spectral properties, rather than linear correlations in a calibration period of the proxy with instrumental observations, provides a great potential to quantitatively estimate the signal recorded in the isotopic composition in ice cores.

Code availability. The code will be made available on mathworks.

Appendix A: Seasonality of Temperature and Precipitation at EDML
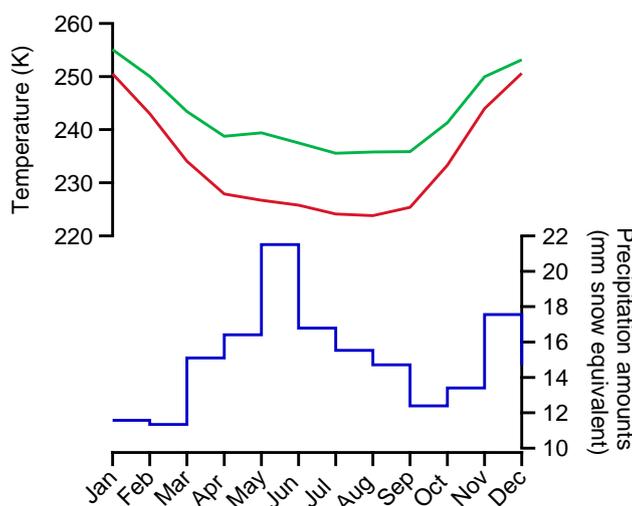
Figure A1. Seasonality of temperature (red), precipitation-weighted temperature (green), and average precipitation (blue) for each month of the entire ERA-interim time series

Appendix B: Illustration of the forward model on Trace21k temperature time series for Dome C

We used the amount of white noise added by precipitation intermittency predicted from the forward modelling approach to simulate the impact of precipitation intermittency over the last 22 000 years (thus neglecting the changes of precipitation patterns due to climate transitions). We converted this $\delta^{18}O$ white noise level predicted for the site of Dome C by the forward model (20.7 ‰^{2}) into a temperature variance using the $\delta^{18}O$ to temperature conversion we applied in the forward model (0.46

‰ °C^{-1}). The noise was added in the temporal domain to match the threshold obtained in the spectral domain. To isolate the impact of precipitation intermittency on the Dome C ice core, we calculated block-averages at the sampling resolution of the Dome C ice core (55 cm), converted time using the present accumulation (9.5 cm s.e., yielding a time resolution of 5.8 a), and neglected snow densification and thinning, changes in accumulation rates, and dating uncertainty.

In the forward model, we added the impact of diffusion to the intermittent virtual core (before sampling to the ice core resolution). The depth-dependent transfer function of diffusion was calculated only within the firn, and the value at the lock-in depth was kept constant, which is a good approximation considering the low isotopes diffusivity in solid ice (Pol et al., 2014).

Author contributions. MC and TL designed the research. MC performed the analysis and wrote the first draft of the paper. MC, TM, and TL contributed to the interpretation and to the preparation of the final paper.

Competing interests. The authors declare no competing interests.

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