



Stratigraphic noise and post depositional effects in isotopic record of Antarctic firn: insights from a snow trench at Dome C

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Abstract. Water isotopes are a key tool to reconstruct past climate variations from ice core records. At sites with low precipitation amounts, such as in Central Antarctica, redistribution by wind and post-depositional processes can alter the snow isotopic signal. This causes a shift in mean isotopic composition and adds stratigraphic noise, with a large spatial variability at the meter scale. In turn, this can modify the isotope-temperature relationship at inter-annual timescales. Here, we present a new dataset of water stable isotope measurements performed on 39 simultaneous 1.5 m deep snow pits dug along a 50 m trench in December 2019 at Dome C. It is combined to timeseries of observed isotopic composition in precipitation and surface-snow conducted over the last decade in order to study the isotope transfer function during snow archival processes. The trench isotopic records covering about 20 years depict no annual cycle and no correlation with local temperature, contrary to precipitation and surface snow time-series. Trench profiles show a very large spatial variability of the inter-annual signal archived in snow. The trench mean $\delta^{18}\text{O}$ values show a +7 ‰ offset (-6 ‰ for d-excess) compared to mean precipitation values, and +2 ‰ offset for $\delta^{18}\text{O}$ (-1 ‰ for d-excess) compared to surface snow, indicating vapour exchanges acting beyond the surface snow layer. The power spectra of trench profiles imply a stronger smoothing at high frequencies than predicted by classical diffusion models. Individual trench profiles are dominated by stratigraphic noise, with a signal-to-noise ratio less than 0.35 across frequencies. This signal-to-noise ratio can be enhanced by up to 50 % by inter-profile alignment based on chemical tracers. The aligned core stack signal shows a multi-annual signal with some features not reproduced by a simple precipitation stacking model, hinting to a contribution of post-depositional effects in this common signal.



1 Introduction

Ice cores in Antarctica are one of the key records to study past climate variations due to their large number of proxies which enable to study and understand climate dynamics at multi-millennial time scales (EPICA community members, 2004; Jouzel et al., 2003). Deep drilling of 3 km long ice cores in Antarctica produces records spanning several hundred thousands years (Petit et al., 1999; Kawamura et al., 2017). Deep drilling sites are typically located in areas where the ice is horizontally stratified (Siebert et al., 1998; Cavitte et al., 2018; Parrenin et al., 2017), with successive core sections representing layers of preserved snow stacked on top of one another. The stable water isotope composition of the ice is classically used as a proxy for past temperatures (Dansgaard, 1964). Past global temperature reconstructions from polar ice and other climate archives, coupled with the past atmospheric composition reconstructed from the air trapped in ice cores (PALAEOSSENS Project Members, 2012), provide key empirical constraints on the uncertainty range associated with the climate system sensitivity (Sherwood et al., 2020), which is used to narrow future climate change projections (Intergovernmental Panel on Climate Change (IPCC), 2021; Jouzel, 2014; Cooper et al., 2026).

Water isotopes are used to reconstruct past temperatures because the abundance of heavy water isotopes in precipitation is driven by Rayleigh distillation which preferably removes heavier isotopes from the air parcel along successive precipitation events, leading to depleted precipitation samples in the centre of the ice sheet compared to the ocean mean (Dansgaard, 1964). This fractionation is temperature-dependent, with more heavier isotopes escaping the water vapour component of the air parcel relatively to the lighter ones under cold conditions. This allows to correlate isotopic concentrations with local temperatures at ice core drilling sites (Jouzel and Merlivat, 1984), supported by present day observation in precipitation (Dreossi et al., 2024). The second order isotopic parameter, δ -excess, tracks differences in isotopic ratios of the main water isotopes due to kinetic fractionation processes in particular related to origins of air masses (Risi et al., 2013) and drivers of evaporation conditions at moisture sources (Merlivat and Jouzel, 1979; Pfahl and Sodemann, 2014). Global circulation models (GCM) equipped with water stable isotopes have been used to investigate past precipitation isotope-temperature relationships accounting for e.g. changes in moisture origin or precipitation intermittency (Werner et al., 2018). Climate reconstructions based on present-day spatial isotope-temperature gradients in transects across Antarctica (Masson-Delmotte et al., 2008) have been applied to quantify temperature variations at glacial-interglacial time-scales (EPICA community members, 2004).

However, in low accumulation sites, the isotopic composition of surface snow can deviate from a local temperature-driven isotopic signal, especially at timescales below decadal, because of the wide range of processes affecting the isotopic composition after the deposition of snow. The fact that precipitation does not occur regularly and with variable amounts creates an aliasing effect in the recorded temperatures, known as precipitation intermittency or precipitation weighting (Casado et al., 2020; Münch et al., 2021; Persson et al., 2011). Past changes in precipitation seasonality could result in changes in the isotopic record that are not driven by temperature (Krinner and Werner, 2003; Delaygue et al., 2000; Dallmayr et al., 2025). Further, the contribution of drifting snow (Stenni et al., 2016) from a nearby location, as well a local snow redistribution by wind (Ekaykin et al., 2002; Picard et al., 2019; Zuhr et al., 2021) can reduce the correlation between the isotopic composition of the accumulated snow and local temperature. This mechanical mixing and uneven deposition at the surface, appearing as



sastrugi several tens of centimetres high, result in high spatial variability in nearby records, called stratigraphic noise (Fisher et al., 1985; Hirsch et al., 2023). The interpretation of the snow isotopic signal based on precipitation alone has been further challenged by the identification of vapour exchange at the snow-atmosphere interface and within the firn, which influences the isotopic composition after deposition. Net sublimation or condensation fluxes at the surface can amount to 10 % of the surface mass balance (Genthon et al., 2017) and are associated with isotopic fractionation (Casado et al., 2018; Wahl et al., 2021; Steen-Larsen et al., 2014; Ollivier et al., 2025b; Casado et al., 2016). At the end of the summer season, temperature gradients in the near-surface snow drive interstitial vapour fluxes associated with additional fractionation and grain coarsening, called snow metamorphism (Casado et al., 2021; Harris Stuart et al., 2023). Finally, the diffusion of the isotopic signal in the firn and more precisely, through the interstitial air matrix causes a smoothing of the signal as it is buried deeper and deeper (Johnsen et al., 2000; Gkinis et al., 2014). Consequently, a single ice core isotopic content is characterised by a complex transfer function, especially at multi-annual and decadal scales, with only a fraction of the original climatic signal, a high amount of noise, potentially some offset in mean values, and smoothing effects.

In this study, we evaluate how to demodulate this complex transfer function for the site of Dome C, taking advantage of three unique datasets: the isotopic composition from trench profiles covering the last 20 years, and a decade of precipitation and surface snow isotopic composition weekly samples. This exhaustive dataset enables us to highlight the signal attributed to precipitation, how it is modified near the surface by the combination of precipitation intermittency, wind redistribution, and post-depositional processes (namely sublimation, solid condensation, and metamorphism), as well as how the signal is further modified below the surface as it is archived. The goal here is to quantify processes that are still unaccounted for in our understanding of archiving of the isotopic signal, such as represented in the Virtual Firn Core model (VFC) (Casado et al., 2020; Leroy-Dos Santos et al., 2023). Our trench record indeed shows greater inter-annual variability than the VFC, with three enriched layers spanning multiple years which cannot be reproduced using a simple precipitation stacking model. This can only be explained through the contribution of post depositional processes to the overall trench record. We quantify the effect of post-depositional modifications of the isotopic content on the signal-to-noise ratio (SNR) (Sec. 3.5), and find that stratigraphic noise is the main driver of the isotopic signal at inter-annual scales in individual pits. Lastly, we highlight missing smoothing in the near surface isotopic composition compared to the classical diffusion model of Johnsen (Johnsen et al., 2000). Overall, multiple evidence confirm that the signal recorded in the trench contains a large noisy component led by stratigraphic noise and post-depositional processes.

2 Methods

2.1 Description of the trench and sampling

The study site, Dome C, is located in East Antarctica (75.1° S, 123.3° E), at an altitude of 3233 m, and is the location of the permanent research station Concordia. The local meteorology is characterised by a mean temperature of about -52 °C (Genthon et al., 2021), accumulation rate of 24 kg m⁻²yr⁻¹ (Genthon et al., 2016; Ooms et al., 2026) and mean wind speed of 4 m s⁻¹ (Genthon et al., 2021). In December 2019, we sampled 39 snow profiles from a 50 m long and 1.5 m deep snow trench. The



trench was dug roughly 1 km upwind from the Concordia station, near the clean area. It was dug purposefully perpendicular to the main wind direction and sampled facing toward origins of wind to minimise contamination by blowing snow. The profiles were sampled at resolutions varying between 1.5 and 3 cm (between 50 and 100 samples per profile), and analyzed for trace ions, physical properties (snow specific surface area (SSA), density and snow micro-pen penetrometer (SMP)) (Ooms et al., 2026) and for stable water isotopes ($\delta^{18}\text{O}$ and δD , this study). We report the snow isotopic composition with the delta notation in per mil (Craig, 1961) with respect to the Vienna Standard Mean Ocean Water (VSMOW) (Gonfiantini, 1978). Here, we focus on $\delta^{18}\text{O}$ and the second order parameter d-excess = $\delta\text{D} - 8 \times \delta^{18}\text{O}$.

Snow profiles in the trench are labeled by the letter P followed by the distance to the first profile P0 (Ooms et al., 2026). The profiles were separated by 2 m in the bulk of the trench, and finer horizontal resolution (10 cm to 1 m) were obtained in three 3-5 m section (at the beginning, the end and on a dune). In total, 30 profiles were sampled at 3 cm resolution, and 9 profiles (P-0.3, P0, P0.1, P0.3, P1, P47.7, P48, P48.1, P48.3) at 1.5 cm resolution (The high-resolution profile P1 had only 3 cm resolution sampling for chemistry, which was used for aligning and dating the profiles, but this has no impact on the results as it was excluded from the trench stack). All of the profiles have been measured at Alfred Wegener Institute (AWI) in Potsdam, Germany. Samples were measured with a Picarro isotopic water analysers (model L2130-i and L2140-i) calibrated on the VSMOW-SLAP scale.

2.2 Alignment and dating

At Dome C, uneven snow deposition induces spatial variability in widths of annual layers at the meter to decameter scale (Picard et al., 2019; Genthon et al., 2016; Ooms et al., 2026), with a standard deviation of about 20 % of the mean accumulation rate. This creates offsets in archival depths of snow layers that can build up over several years, or even longer time scales (Barnes et al., 2006). Multi-annual signals from snow tracers are therefore unevenly recorded in individual profiles, and hence partially lost when averaging neighbouring profiles based on physical depth scale.

To mitigate this effect, an inter-profile alignment based on chemical tracers (mainly sulfate) and snow physical properties was performed (Ooms et al., 2026). The alignment accuracy is around 3 cm, taking into account the probability for hiatus (i.e. missing snow layers) (Ooms et al., 2026; Picard et al., 2019). Next, Ooms et al. (2026) constructed an age depth model for the trench by matching the trench sulfate profile stack with older snow pits dug in the 2000-2019 period. Note that the trench could not be dated using volcanic eruptions since no major volcanic sulfate peak was detected. Indeed, the chemical fingerprint of the Pinatubo eruption would be archived roughly a meter below the bottom layer of the trench. The overall uncertainty of the dating is estimated to be around 1 year (Ooms et al., 2026), attested by the relatively good alignment corresponding with a high wind event in 2015 as indicated by a harder snow layer. The bottom of the trench is estimated to contain snow accumulated in early 1999, meaning that the trench represents about 20 years of snow record across a 50 m long transect.

The vertical scale of the trench profiles was recorded on an absolute depth scale (denoted z) relative to a common zero via horizontal laser alignment. Together, alignment and dating allow us to project all profiles in the trench from the depth axis onto a common time axis via linear squeezing and stretching. We refer to this picture as the *aligned* trench, which would be the equivalent of an ice core for which annual layer counting was available for dating purposes. Another configuration is obtained



by setting the surface height to zero to put profiles together on a common depth axis. This simpler alignment based on depth is referred to as the *levelled* trench. The levelled trench is then given a simple time axis based on the mean snow accumulation rate of 7.5 cm yr^{-1} (Fig. A4) (Ooms et al., 2026). This would be equivalent to an ice core for which dating could only be done by identifying volcanic peaks every 20 to 50 years, with a linear interpolation in between tie points.

2.3 Additional datasets

Snow pits presently sampled at Dome C can be compared with precipitation and surface snow sampling that have been conducted on site for more than a decade. Precipitation isotopic composition has been monitored daily at Dome C since 2008 (Stenni et al., 2016; Dreossi et al., 2024; Ollivier et al., 2025b) and surface snow bi-weekly since 2014 (Casado et al., 2018, 2021; Ollivier et al., 2025b). In addition to the isotopic composition, precipitation amounts are also available for the periods 2008-2010 (Stenni et al., 2016) and 2017-2022 (Ollivier et al., 2025b). While the absolute value of sampled precipitation amount is 50 % lower than accumulation rates observed with stake farms (Genthon et al., 2016; Stefanini et al., 2025) and reconstructed from chemical firn stratigraphy (Ooms et al., 2026), we use this dataset for precipitation weighting and to compare it with the variability of precipitation amounts in ERA5, assuming that the amount measured is proportional to the actual amount of snow fall on that day (Ollivier et al., 2025b; Kopec et al., 2019).

Precipitation samples follow a strict collection protocol in order to record their initial isotopic composition as accurately as possible. The sampling site is located in a clean area upwind from Concordia station and the sampling platform is shielded to reduce contamination by blowing snow from the surface. Precipitation is collected every morning within a 3 hour window (9:00 to 12:00 local time, UTC+8), and the platform is subsequently cleaned for the next day, unless prevented by adverse weather conditions, which rarely occurred (Stenni et al., 2016; Dreossi et al., 2024). Despite regular sampling, snow can remain exposed for up to 24 hours, during which time the isotopic composition might change due to sublimation or condensation on the collection table. Consequently, the measured precipitation might differ from the initial precipitation input. Moreover, even with protective shielding the platform can collect blowing snow, which is affected by airborne isotopic fractionation (Wahl et al., 2024). To account for this, Ollivier et al. (2025b) used a criteria of d-excess $< 0 \text{ ‰}$ to discard samples, which mostly affects summer snow samples. For the periods 2008-2010 and 2017-2022, where precipitation amounts are available, this criteria discards 10 % of data, and 9 % of the precipitation amounts. To further rationalise the isotope-temperature relationship in precipitation, we strengthen the criteria by also excluding d-excess values above 30 ‰ . This will mostly impact winter values that show a strong depletion in $\delta^{18}\text{O}$, and which are associated with extremely low precipitation events. Consequently, this second constraint excludes additional 12 % of data, but only 2 % of precipitation amounts (2008-2010 and 2017-2022). All the analyses presented in this manuscript are based on this restricted precipitation dataset. This also applies to the fitting of the isotope-temperature relationship as the input to the VFC model (Sect. 2.4.1). We conduct sensitivity tests show that our conclusions are unchanged without the restriction criteria (Appendix Section A1).

Each surface snow data point represents the average of two samples collected at two random locations 50 m apart. This averaging removes some of the local noise such as uneven accumulation, blowing snow or topography dependent vapour exchanges. This protocol reduces the time series variability and can affect the comparison of this dataset with our trench



Data	Time covered	Sampling rate	Reference
Precipitation	2008-2022		
	2008-2017	daily	Stenni et al. (2016); Dreossi et al. (2024)
	2017-2021	daily	Ollivier et al. (2025b)
Surface snow	2011-2012 & 2013-2022		
	2011	daily	Touzeau et al. (2016)
	2012 and 2014	weekly	Casado et al. (2018)
	2013-2016	tri-weekly	Casado et al. (2018)
	Dec 2014-Jan 2015	daily	Casado et al. (2018)
	2017-2021	bi-weekly	Ollivier et al. (2025b)

Table 1. Summary information for in situ observations of surface snow and precipitation at Dome C.

dataset. There is evidence of lower data quality in 2011-2012 due to a slightly different sampling protocol, so we only use the continuous surface snow time series covering the period from the end of 2013 to the present.

To compare mean values, we thus focus on the periods 2008-2019 for precipitation and 2014-2019 for surface snow as these periods overlap with that covered by the trench profiles. For the spectral analysis, we have used the full available series covering 2008-2022 and 2014-2022 for precipitation and surface snow to extend the spectra. The impact of the selected period is limited and does not influence the results (Supplements, Figure S1). Table 1 provides a summary of all the observation campaigns.

2.4 Numerical methods

2.4.1 Simulation of precipitation, surface snow and firn cores

In order to compare the trench dataset against the signal expected from the relationship between precipitation isotopic composition and local temperature, we construct Virtual Firn Core (VFC) isotope profiles (Casado et al., 2020; Leroy-Dos Santos et al., 2023). For this purpose, we use the ERA5 reanalysis (Hersbach et al., 2020) precipitation amounts, with a scaling such that the total snow accumulation in the period 2000-2019 is $24 \text{ kg m}^{-2} \text{ yr}^{-1}$ as inferred from observations at Dome C and trench data (Genthon et al., 2016; Ooms et al., 2026). The $\delta^{18}\text{O}$ values of the input precipitation for the VFC are calculated from a linear fit of the daily 2 m temperature of ERA5, T_{2m} , to the daily precipitation samples isotopic composition for the period 2008-2022 (Dreossi et al., 2024; Ollivier et al., 2025b). The d-excess - $\delta^{18}\text{O}$ relationship for Dome C is calculated only from the precipitation isotopic composition. We applied the d-excess exclusion criteria discussed in Section 2.3 for both fits (total of 1692 samples);

$$\delta^{18}\text{O}_{T_{2m}}(\text{‰}) = 0.47 (\pm 0.01) \cdot T_{2m}(\text{°C}) - 32 (\pm 0.5) \quad (r^2 = 0.56) \quad (1)$$



$$d\text{-excess}_{T_{2m}}(\text{‰}) = -0.78 (\pm 0.02) \cdot \delta^{18}\text{O}_{T_{2m}}(\text{‰}) - 28 (\pm 1) \quad (r^2 = 0.45) \quad (2)$$

The input for surface firn temperature is prescribed by the seasonal average for Dome C (Touzeau et al., 2016; Laepple et al., 2018):

$$T_{\text{surf}}(t) = T_0 + A_1 \cos(\omega_{\text{yr}}t) + A_2 \cos(2\omega_{\text{yr}}t) \quad (3)$$

where ω_{yr} represents the yearly angular frequency, $T_0 = -54.9^\circ\text{C}$, $A_1 = 17.4^\circ\text{C}$, $A_2 = 6.3^\circ\text{C}$. We consider a $\pm 2^\circ\text{C}$ sensitivity test on the parameter T_0 for our results to also be consistent with more recent surface temperature observations at Dome C (Lupi et al., 2021; Ollivier et al., 2025a). The comparison of Equation 3 with observational datasets is given in the appendix Section A2. The firn temperature profile is resolved in depth with the heat transfer equation solution for harmonic conditions at the boundary, constant thermal diffusivity and negligible heat advection (Paterson, 1994).

We run the VFC with the ERA5 inputs for total precipitation amounts, and the precipitation isotopic composition given in eq.(1) and (2), for the period 1999-2019. The model captures the precipitation weighting of the input signal and incorporates the densification model of Herron-Langway (Herron and Langway, 1980), and the effect of interstitial diffusion (Johnsen et al., 2000), taking into account the seasonal variability in upper firn temperature (Laepple et al., 2018). We focus on the deterministic part of the firn core signal, and we do not attempt to model stratigraphic noise by adding white noise, as done in Casado et al. (2020). We use the VFC as an ideal representation of a climatic record of layered precipitation, to quantify how much trench data deviates from this idealised precipitation input. From the VFC, we also extract a virtual surface snow (VSS) time series for the period 1999-2019, by recording the average value of the top 1 cm of the VFC at each time step, assuming a surface density of 320 kg m^{-3} (Genthon et al., 2016; Ooms et al., 2026). This approach is completely analogous to the Snow Isotopic Signal Generator (SISG) described by Ollivier et al. (2025b).

2.4.2 Signal analysis

In order to evaluate the amount of stratigraphic noise affecting single trench profiles, we compute the signal-to-noise ratio (SNR) of the trench record. We evaluate the SNR for both the aligned and levelled trench stacks (Section 2.2) to estimate the effect of the alignment on the SNR. The frequency domain SNR is computed following Münch and Laepple (2018). For a stack of n snow cores x_i , $i = 1, \dots, n$, the power spectral density (PSD) of the mean, S , and the mean of power spectral density, M , read as in Eq. 4-5

$$S = \text{PSD}\left(\frac{1}{n} \sum_i x_i\right), \quad (4)$$

$$M = \frac{1}{n} \sum_i \text{PSD}(x_i). \quad (5)$$

The noise level N and the common signal C are then given by the expressions in Eq. 6-7,

$$N = \frac{n}{n-1} (M - S), \quad (6)$$



$$C = \frac{n}{n-1} \left(S - \frac{1}{n} M \right). \quad (7)$$

The spectral SNR for a given sampling period Δt (SNR_{PSD} , Eq. 8) is defined as the ratio of the integrals of C and N from the lowest frequency to the Nyquist frequency $f_{\text{Nyq}} = \frac{1}{2\Delta t}$ of this sampling period,

$$\text{SNR}_{\text{PSD}} = \frac{\int_{f_0}^{f_{\text{Nyq}}} C(f) df}{\int_{f_0}^{f_{\text{Nyq}}} N(f) df}. \quad (8)$$

We note that this is mathematically equivalent to the correlation based $\text{SNR}_r = \frac{r_{XY}}{(1-r_{XY})}$, where r_{XY} is average value of the $n \cdot (n-1)/2$ possible cross-correlation coefficients between the time series averaged at a given sampling period Δt (Fisher et al., 1985; Laepple et al., 2018). For the levelled stack, we compute the power spectra in depth domain, and convert them to time domain with a constant accumulation of $24 \text{ kg m}^{-3} \text{ yr}^{-1}$ (7.5 cm yr^{-1} snow).

2.4.3 Computation of the diffusion length

Firm isotopic diffusion acts as a low pass filter represented by a convolution with a Gaussian kernel, whose standard deviation is given by the diffusion length. According to the Johnsen model (Johnsen et al., 2000), the diffusion length increases up to the lock-in depth, after which snow compaction slightly reduces the diffusion length at higher depths. The diffusion length can be estimated from the power spectral density of the isotopic profile, as it will determine the slope of the decreasing spectral powers at higher frequencies (Grisart et al., 2022). More specifically, if A_0 and A are the amplitudes of the spectra with and without diffusion, we have the relationship as in Eq. 9 (Gkinis et al., 2014),

$$A = A_0 \exp(-2\pi^2 f^2 \sigma^2), \quad (9)$$

where σ is the diffusion length. σ can be obtained from the slope of the linear regression of $\log A$ against f^2 , as Eq. 10

$$\sigma = \frac{1}{\sqrt{2\pi}} \sqrt{|\text{slope}|} \quad (10)$$

We split the depth scale over three depth ranges (0-50 cm, 50-100 cm and 100-150 cm) to compute diffusion lengths. This allows us to evaluate the diffusion at different depths while allowing the computation of spectra from a sufficient number of data points. The fit is performed in the 6 m^{-1} to 9 m^{-1} frequency range and we show that different choices of fitting window do not influence the result (Section A6). We apply this analysis to all trench profiles, and report the mean and 95 % confidence interval for the estimated diffusion. We then compare the observed diffusion lengths to the Johnsen model with surface snow density 320 kg m^{-2} , snow accumulation of $24 \text{ kg m}^{-2} \text{ yr}^{-1}$ and mean seasonal temperature with two harmonics (Equation 3). In the diffusion length estimation from the trench data, σ is assumed to be constant, thus represents an average value over the depth range considered that does not represent an arithmetic average. To account for this in the comparison with the Johnsen model, we calculated diffusion length with our method on white noise profiles diffused with a known diffusion length (Section A6). We conclude from this comparison that the estimated diffusion length is robust and representative of the highest diffusion length in a given depth section.



3 Results

3.1 Trench isotopic composition variability

The 2-D picture of snow isotopic composition in the trench exhibits a pronounced spatial variability which contradicts the view of a homogeneous layering of seasonal snow layers (Fig. 1a for $\delta^{18}\text{O}$ and Fig. 1e for d-excess). The $\delta^{18}\text{O}$ values ranges from -58 to -43 ‰, while the d-excess values range from -6 to 18 ‰. The independently dated isochrones of Ooms et al. (2026), obtained from chemical tracers, are laid on top of the trench. While the trench covers 20 years, there is no seasonal pattern in the vertical profiles. Instead, we can only identify three remarkable maxima spaced by either 25 or 75 cm, corresponding to several years of accumulation (Casado et al., 2018; Laepple et al., 2018). The mean background value is around -51 ‰ on which the three enriched layers (2003, 2014 and 2018) reach more than -48 ‰. For d-excess, we observe an overall mean background value of 9 ‰, with two remarkable low d-excess layers in 2015 and near the surface (2019) reaching down to -5 ‰. The trench includes a 30 cm high dune in the 40-50 m section. The isochrones mirror the surface dune topography in the entire depth of the trench, hinting at a persistence of this dune for at least 20 years (Ooms et al., 2026). The isotopes also seem to follow these isochrones, indicating that the enriched layers were evenly deposited across the trench. This is especially visible in the $\delta^{18}\text{O}$ 2003 layer (150-175 cm depth) which follows a $\delta^{18}\text{O}$ enriched layer across the trench, as well as in the d-excess 2015 layer. We then produce a mean trench profile on a time axis by averaging horizontally along the isochrones (Fig. 1b,f). The average is calculated on the subset of 26 independent profiles evenly distributed 4 m apart (Section 3.2). The mean $\delta^{18}\text{O}$ in the trench is -49.7 ± 0.3 ‰ (mean $\pm$ standard error). For comparison, five snow pits 1 m to 2.5 m deep, dug in 1977-2015 at Dome C (Touzeau et al., 2018; Casado et al., 2018), give average $\delta^{18}\text{O}$ values of 50.5 ‰.

To compare the isotopic content of the trench with that of an ideal climatic record, we consider the simple layered precipitation model of the ERA5 VFC. The VFC prior to diffusion (Fig. 1c, g) exhibits 6-9 cm annual layers, which corresponds to the seasonal cycle since the local accumulation rate is 7.5 cm snow equivalent. If we add in the effect of Johnsen diffusion to the VFC, many summer extreme values are lost, with a stronger effect at lower depths where only a 2002 maximum stands out in diffused VFC $\delta^{18}\text{O}$ (Fig. 1d, h), but the VFC still contains seasonal layers. This is very different from the mean trench profiles, where only three high $\delta^{18}\text{O}$ layers stand out in the mean $\delta^{18}\text{O}$ trench profile in 2003, 2014 and 2018 and one low d-excess layer in 2015 (Fig. 1b, f), with highly reduced amplitudes compared to the individual trench profiles. The 2003 and 2014 enriched layers in the trench seem to coincide with maximum $\delta^{18}\text{O}$ values of the raw VFC output, but do not stand out as remarkable features after accounting for diffusion.

The Dome C trench shows less spatial regularity than two trenches sampled near EPICA Dronning Maud Land (EDML) drilling site (75.0° S, 0.1° E; 2891.7 m), characterised by higher mean annual temperatures of -44.5 °C; and more than twice the accumulation rate than Dome C ($64 \text{ kg m}^{-2} \text{ yr}^{-1}$) (Münch et al., 2016; Wesche et al., 2007). Those trenches are 45 m long and 1.2 m deep and depict horizontal positive and negative anomalies associated with five successive visible seasonal cycles spanning about 20 cm each. By contrast, the layers are not homogeneous across the entire Dome C trench. If we consider the subset of 26 profiles evenly distributed every 2 meters, the enriched $\delta^{18}\text{O}$ layer of 2014 is missing in 8/26 or 35 % of profiles, and the 2003 layer is missing in 6/26 profiles, or 25 % of the profiles. This is consistent with the snow accumulation



hiatus observed by Ooms et al. (2026), where we showed chances as high as 40 % for a 6 month layer to be missing (with a corresponding accumulation amount less than the 3 cm sampling resolution of the trench), also consistent with the laser scanner surface observations of Picard et al. (2019).

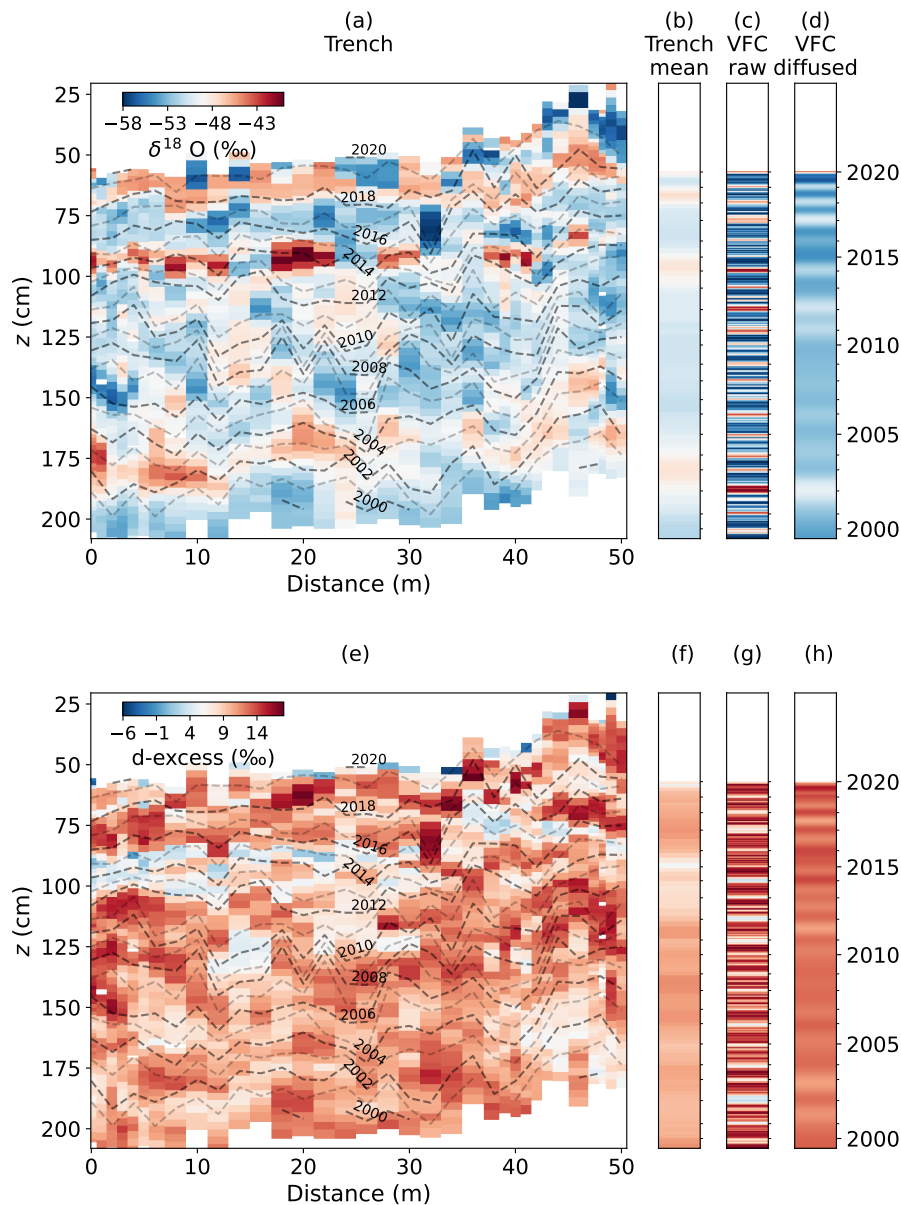


Figure 1. Isotopic composition of the 39 trench profiles (a, e), and the isotopic composition of the aligned trench mean profile (b, f) (26 profiles evenly distributed) next to the isotopic profile of VFC prior to diffusion (c, g) and after diffusion and 1 cm block average (d,h). Upper panel (a, b, c, d) shows $\delta^{18}\text{O}$ and lower panel (e, f, g, h) shows d-excess. The VFC input has been tuned to a mean accumulation rate of $24 \text{ kg m}^{-2} \text{ yr}^{-1}$ (7.5 cm yr^{-1} snow equivalent) and (c, d) and (g, h) are in the same homogeneous depth scales as (a) and (b), with the same surface height as P0. The corresponding inhomogeneous age scale for the VFC is shown on the right axis, and the mean aligned trench profiles (b, f) are fitted on this scale.



3.2 Spatial correlation patterns and construction of the trench stack

270 In the trench, we observe highly variable isotopic profiles, even at short distance (Fig. 1a, e). The horizontal $\delta^{18}\text{O}$ variance in the raw trench is $4.8 (\text{‰})^2$ (considering horizontal levels from all 39 individual profiles). The variance is nearly identical in the levelled trench, at $4.7 (\text{‰})^2$. This poses the question of the representativity of single trench profiles. We assess this from inter-profile correlation analyses. Following Ooms et al. (2026), we consider both aligned and levelled configurations of the trench (Method, Section 2.2). The mean pairwise correlation in the levelled trench is 0.11, while the mean pairwise correlation
275 in the aligned trench is 0.17. To resolve the spatial inter-correlation structure and decorrelation length, we consider the mean of all pairwise correlation coefficients for profiles separated by a given distance (Figure 2). Between 0 to 10 m distances, we observe an exponential decrease of the correlation in both aligned and levelled trenches, with a decorrelation length of 1.2 m. This is slightly shorter than the decorrelation length of sulfate of 1.4 m, which was used in Ooms et al. (2026) for the trench alignment. Beyond 10 m distances, we see different decreasing patterns. In the levelled trench, the correlation drops to zero
280 after 20 m, corresponding to the horizontal scale of the dune. By contrast, profiles retain a 0.2 correlation on average up to 30 m apart in the aligned trench. This is smaller than the long distance correlation of 0.3 for sulfate profiles in the trench (Ooms et al., 2026) used for the alignment. This result indicates that more processes affect the isotopic composition after precipitation than chemical signals after their deposition. This is also very different from the results obtained in the trench at the higher accumulation site EDML (Münch et al., 2016), where profiles are characterised by a higher correlation coefficient of 0.5 at
285 decameter scale.

In order to make a stack for which the signal to noise ratio will be increased, thus for which the noise component is decorrelated among profiles, we need to stack individual records located at a distance beyond the decorrelation length λ . Here, considering our spatial sampling, we choose to include profiles separated by 2 m. In the next sections, we focus on the subset of 26 profiles 2 m apart, instead of the full initial set of 39 profiles. We refer to this subset as the trench stack. All subsequent
290 results, including mean values, trench time series and their spectral analysis will be based on this stack of 26 profiles.

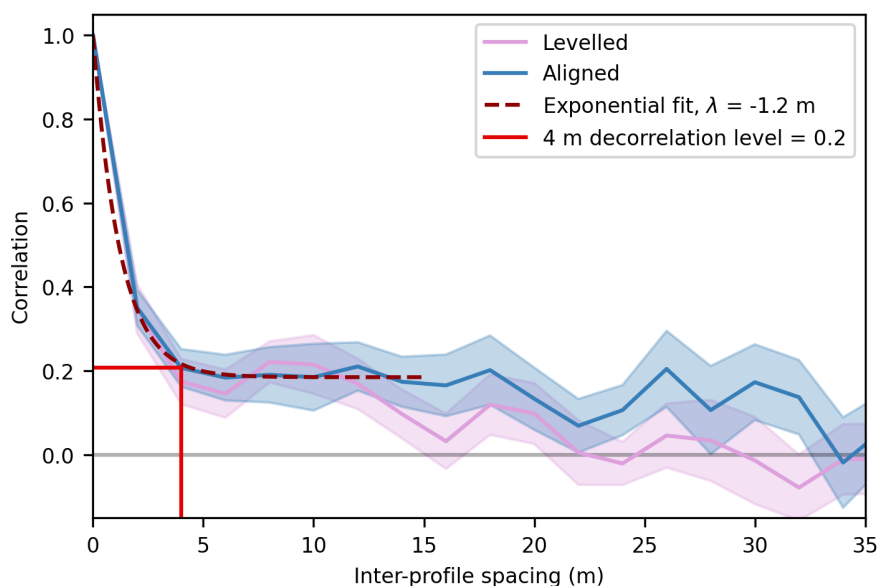


Figure 2. Spatial decorrelation pattern in the trench. Inter-profile correlation is plotted against inter-profile distance, showing an exponential decrease at large distances. Both aligned trench (blue) and levelled trench (pink) are shown. The envelope shows the standard error on the mean, indicating that the mean correlation is not significantly different from zero beyond 20 m for the levelled trench, and beyond 32 m for the aligned trench.

3.3 Shifts in mean isotopic composition from precipitation to surface snow and to upper firn

The average isotopic values in the precipitation, surface snow and trench datasets over the overlapping period (2014-2020) are represented in Figure 3 (coloured markers in panels b and d). Over this period, the mean isotopic composition of the surface snow shows a +4.9 ‰ difference in $\delta^{18}\text{O}$ and -5.2 ‰ in d-excess compared to the averaged precipitation signals. The mean value in the trench shows an additional +2.2 ‰ in $\delta^{18}\text{O}$ and -0.8 ‰ in d-excess, for a total of +7.1 ‰ and -6.0 ‰ relative to precipitation, respectively. Mean values over other periods of interests are reported in Table A1 in the Appendix, and yield similar differences.

Besides these systematic offsets in mean values of observational datasets, we calculated mean values for the intermediate step of archival corresponding to precipitation weighted signals. Most trench samples represent 3 cm of snow accumulation, giving higher weights to values associated with large precipitation events. We estimate this effect to +3 ‰ in $\delta^{18}\text{O}$ and -2.5 ‰ in d-excess by comparing the average values in the precipitation input of the VFC and the virtual firn core over the period (2014-2019) (Figure 3b, d, black diamond markers). Surface snow samples are also subject to this effect, since they average over the most recent 1 cm of precipitation, which represent 1-2 months of accumulation. The effect of precipitation weighting might not be identical in mean values of surface snow and firn cores. Indeed, surface snow can be seen as a running window on a firn core with the width corresponding to the surface sampling depth, and this running window is dependent on the accumulation rate. Low accumulation periods indeed lead surface snow to be exposed for longer time than during high accumulation periods,



potentially skewing the average value of the entire time series by over-representing the isotopic composition of surface snow associated with lower accumulation. We tested this effect with the VFC model by comparing the mean values in the VSS and in the VFC (Figure 3b, d, black underscore markers). We found a $+0.2\text{‰}$ change in $\delta^{18}\text{O}$ (-0.2‰ decrease in d-excess) from the VSS to the VFC, which is much smaller and insignificant compared to the difference of several ‰ in average values of observations, as well the overall contribution of precipitation weighting. To further improve the robustness of precipitation weighting estimates, we follow Ollivier et al. (2025b) and calculate mean values of weighted precipitation estimates for the periods when they are available. The results are shown in the appendix section A4 and are in overall agreement with the VFC approach.

To summarise, we observe a $+7\text{‰}$ offset in $\delta^{18}\text{O}$ from precipitation data to the trench data (-6‰ in d-excess) and a $+5\text{‰}$ offset between precipitation and surface snow data (-5‰ for d-excess). We estimated that the effect of precipitation weighting can account for a $+3\text{‰}$ for $\delta^{18}\text{O}$ (-2.5‰ for d-excess). The simple layered precipitation model, which correctly represents the mean value in precipitation observations, fails to account for these large differences between weighted precipitation, surface snow and firn cores.

3.4 Inter-annual variability

We consider the inter-annual variability of the dated trench stack and compare it to precipitation and surface snow time series. We use the VFC model, its isotopic input fitted on ERA5 temperature time series ($\delta^{18}\text{O}_{\text{T2m}}$), as well as the virtual surface snow time series (Section 2.4.1) to assess how much of the original climatic signal is transmitted along the archival process of snow in the upper firn. The $\delta^{18}\text{O}$ precipitation time series is dominated by a clear annual cycle with a high amplitude and symmetrical variations that closely follow temperature variations (Figure 3, green and grey lines). The correlation coefficient of $\delta^{18}\text{O}$ in precipitation with $\delta^{18}\text{O}_{\text{T2m}}$ is $r^2 = 0.56$ (p-value < 0.05) for samples within the d-excess filtered range ($0 \leq \text{d-excess} \leq 30\text{‰}$) and $r^2 = 0.64$ (p-value < 0.05) for all samples in the period 2008-2020. The amplitudes of 15 days averages are about 30 % higher in observations with a range of -67 to -39‰ , against -64 to -44‰ in $\delta^{18}\text{O}_{\text{T2m}}$ for the period 2008-2020. This suggests that roughly 56 % of the variability in the precipitation isotopic signal is explained by local temperature variations. The correlation coefficient for d-excess time series is lower but still significant with $r^2 = 0.20$ (p-value < 0.05) within the filtered range and $r^2 = 0.36$ (p-value < 0.05) for all samples.

In the surface snow time series (Figure 3, orange line), this annual cycle remains present, but its amplitude is mostly reduced to the summer part of the seasonal cycle (-57 to -43‰), as the lower winter values are associated to smaller precipitation amounts that contribute negligibly to the upper 1.5 cm of the snow pack. The analysis of the correlation of isotopic content of surface snow with temperature needs to account for the lag due to the integration of roughly 3 months of snow isotopic composition in such surface snow samples (Casado et al., 2018; Ollivier et al., 2025b). Using the virtual surface snow time series (VSS), we find a correlation between $\delta^{18}\text{O}$ and the precipitation weighted temperature from the VSS of $r^2 = 0.36$ (p-value < 0.05), as well as a correlation coefficient $r^2 = 0.2$ for d-excess (p-value < 0.05). The virtual surface snow time series is presented in the appendix (Section A5). The ranges of surface snow $\delta^{18}\text{O}$ are nearly identical between observations and VSS (-59 to -41‰), but the offset in mean values (Fig. 3b, d) reflects the fact that peaks are broader in the observations than in the



VSS. The amplitudes in d-excess are close, with -5 to 19 ‰ for observations and 4 to ‰ for the VSS, noting that only values from two summer seasons (2015,2016) lie below 5 ‰ for surface snow. Overall, while the temperature signal is still present, we already see strong evidence of post depositional processes acting at the level of the surface.

The picture is very different when we turn to the trench data. The mean of the trench stack (Figure 3a, c, blue line and envelope) is our best attempt to obtain an isotopic time series free of meter scale spatial variability, i.e. separating signals driven by precipitation and stratigraphic noise. We compare this trench stack with the VFC (Figure 3a, c, dashed black line) to which we have applied the Johnsen diffusion model and a 3 cm block averaging to simulate the trench sampling. We observe very different inter-annual variability between these two time-series which are not statistically correlated ($r^2 = 0.1$, p-value = 0.4 for $\delta^{18}\text{O}$ and $r^2 = 0.1$, p-value = 0.5 for d-excess, based on 50 samples at 3 cm resolution). The amplitude of $\delta^{18}\text{O}$ variations is about 20 % higher in the trench mean (-52 to -47 ‰) than in the VFC (-54 to -50 ‰), in addition to a 4 ‰ offset. The range of d-excess is also larger in the trench (5 to 12 ‰) than in the VFC (8 to 14 ‰) again with a systematic -2 to -3 ‰ offset.

The $\delta^{18}\text{O}$ trench stack shows two broad enriched layers in 2003 and 2014 with 3 ‰ anomalies on a background value of -50 ‰. These layers span 2-3 years of accumulation, thus reaching the same amplitude but over a longer span than the annual peaks still present in the VFC after diffusion. A third enriched layer in 2018 is slightly narrower and spans 1 year of accumulation. The d-excess trench stack shows a remarkable layer in 2015 reaching low value of 5 ‰, and several profiles in the trench exhibiting negative values (Figure 1). No such feature is depicted by the VFC where values remain around 13 ‰ in the period 2012-2016. This coincides with a minimum in the observed surface snow time series (-5 ‰) which is not displayed in the VSS.

To conclude, our trench stack exhibits inter-annual variability features that cannot be explained from a simple layered precipitation model. While precipitation and surface snow do show a strong seasonal link with temperature, the archival of the signal in the deeper firn associated with a high spatial variability produces a mean trench isotopic signal that appears to be decorrelated from the initial precipitation signal.

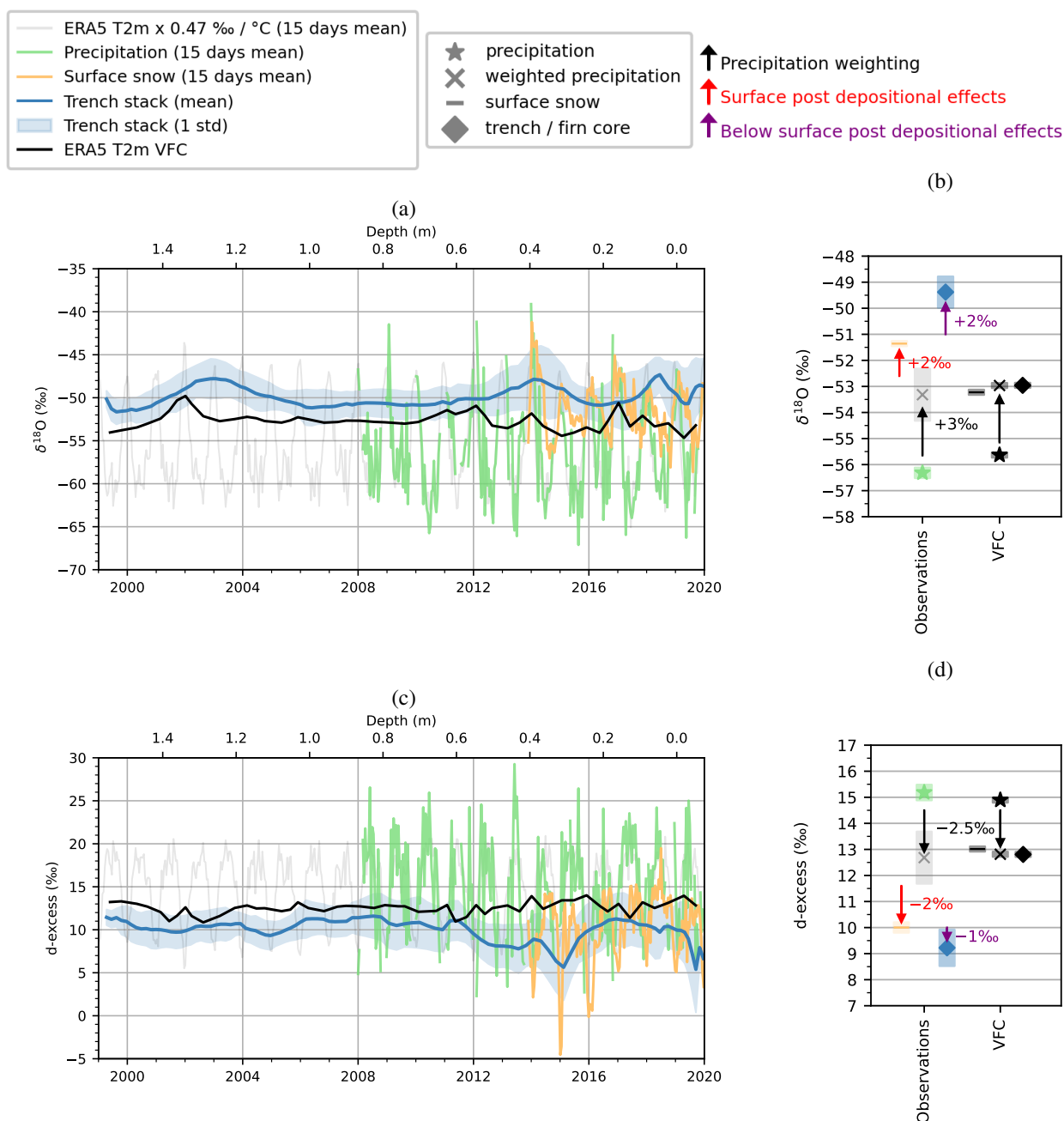


Figure 3.



Figure 3. Mean isotopic time series from the trench stack (blue) compared to surface snow (orange), precipitation (green), temperature time series (grey) and output of the VFC experiment (black) for $\delta^{18}\text{O}$ (a) and d-excess (c) as well as mean values (b and d). The blue envelope represents 1 standard deviation for the 26 independent profiles in the trench stack. The mean values are calculated for the overlapping period 2014-2019 for the observations and for the full period 1999-2020 for the simulated profiles. Mean values are given with star (precipitation), cross (weighted precipitation), horizontal bar (surface) and diamond (trench/firn core) symbols. The weighted precipitation for observations (dark green 'x' marker) is only an indicative value due to the limited data available for measured precipitation amounts. It is set to +3 ‰ for $\delta^{18}\text{O}$ and -2.5 ‰ for d-excess compared to mean values for precipitation, based on measures for the restricted periods (2008-2010, 2017-2019) and VFC experiment (See Table A1).

3.5 Analysis of the common trench signal

365 We compute the SNR of the trench profiles to evaluate how much common signal can be extracted underneath the spatial variability (see Methods Section 2.4.2). We apply the SNR calculation as a function of the timescale to the aligned and levelled trench stack $\delta^{18}\text{O}$. Figure 4 shows the SNR of $\delta^{18}\text{O}$ calculated from a spectral method (SNR_{PSD}) (Münch and Laepple, 2018). The SNR is around 0.35 at decadal scales in the aligned trench, and drops to 0.2 for 6-monthly averages. This is 20-50 % higher than in the levelled trench, where it reaches 0.3 at decadal scales and only 0.11 at 6-monthly averages.

370 This increase in SNR from the levelled trench to the aligned trench shows the effectiveness of profile matching based solely on chemical tracers in recovering a common isotopic signal from the profiles. Since chemical tracers are interpreted as a marker of deposition time, this indicates that the local noise in the isotopic record at high frequencies is linked to the archival of single precipitation events at varying depth levels, also called stratigraphic noise. Combined with the analysis of the mean signal (Section 3.4), we see that not only is the mean signal very different from what is expected from a simple precipitation based

375 temperature record, but also that a single record contains 65-80 % of stratigraphic noise at inter-annual timescales. It is worth mentioning that the precision of the alignment, leading to vertical phase noise equivalent to a year of accumulation, and of the dating of the trench, also around one year (Ooms et al., 2026), limit the increase of SNR gained by alignment at annual time scale, explaining the abrupt drop between 5 and 2 years.

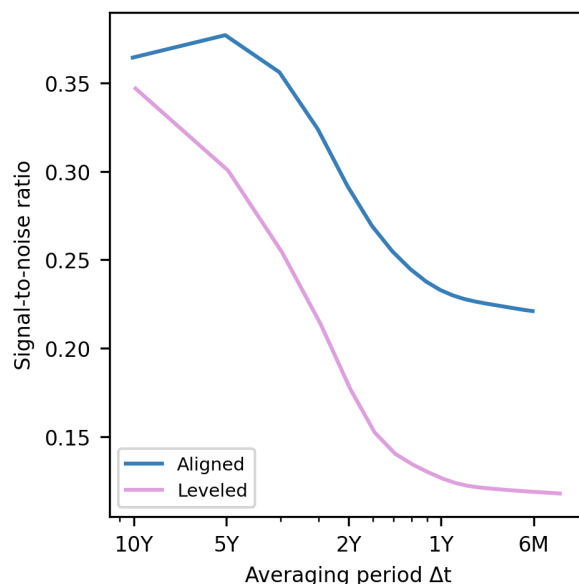


Figure 4. Signal-to-noise ratio (SNR) in the spectral domain for the aligned (blue) and levelled trench (pink). The averaging periods for the levelled trench are calculated in depth domain at 3 cm resolution and converted to time domain with a constant accumulation rate of 7.5 cm yr⁻¹. The solid line gives the spectral approach SNR and the crosses show the correlation based SNR (Section 2.4.2)

3.6 High frequency smoothing

380 We applied spectral analysis to the trench $\delta^{18}\text{O}$ profiles in order to evaluate quantitatively the accuracy of the high frequency smoothing due to firn diffusion over the first 1.5 m of the firn. We perform this analysis using the average of spectra from individual profiles, so only firn diffusion acts as a low-pass filter, and not phase noise due to the limited precision of the alignment. For timescales smaller than 5 years, we observe the typical drop in power spectral densities (PSD) associated with the smoothing at high frequencies of the signal caused by diffusive processes. This reflects the lack of annual layers in the
 385 individual trench profiles (Figure 1a).

We compute estimates for the diffusion length for 50 cm sections of the trench (Section 2.4.3) and compare with results from the Johnsen diffusion model applied to the climatic conditions observed at Dome C (Fig.5.). The diffusion length estimated from the trench in the top 50 cm is 4.0 ± 0.4 cm (95 % confidence interval among profiles) (Figure 5, blue areas), higher than predictions from the Johnsen diffusion model, which gives $2.8 \text{ cm} \pm 0.3 \text{ cm}$ (Figure 5, solid black curve). Here, we compare
 390 it with the maximum value in the depth range, to account for the measurement bias of our method (Section A6). The diffusion length steadily increases with depth and reaches 4.8 ± 0.2 cm at 100-150 cm depth, while the Johnsen model indicates 4.2 ± 0.5 cm. Sensitivity tests were conducted and showed that the results are not sensitive to the frequency range over which the calculation of the diffusion length is performed, nor to the resolution of the vertical profile (Section A6).



Recent studies have suggested that additional mixing should be considered near the surface, characterised with mixing length σ_{mix} which is combined with Johnsen diffusion via the following equation $\sigma = \sqrt{\sigma_{Johnsen}^2 + \sigma_{mix}^2}$ (Samin et al., 2026). This mixing could be mechanical (forced by wind and uneven snow deposition), as modelled by a 4 cm mixing depth in Ollivier et al. (2025a), or result from enhanced vapour exchange due to temperature gradient metamorphism. The difference between the diffusion length estimated from the trench and the Johnsen estimates indicates an additional mixing of 1.7 cm to 3.0 cm (linear regression on the parameter σ_{mix} within the confidence interval of the trench estimates).

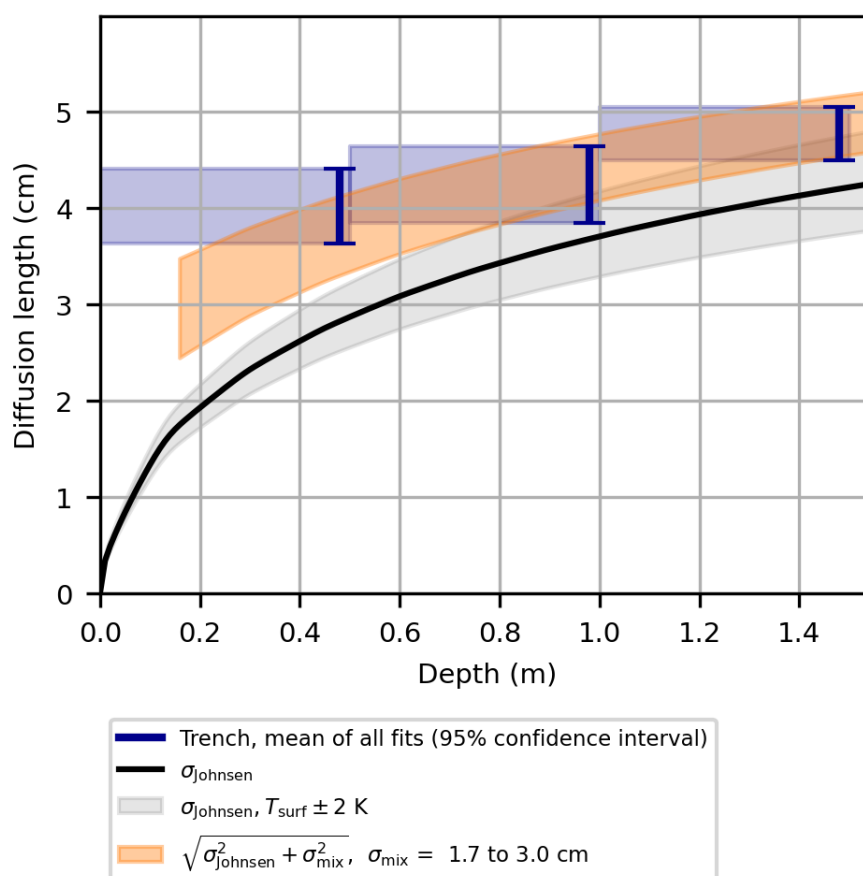


Figure 5. Diffusion length calculated from a linear fit on the trench profiles power spectra for different depth ranges. Shaded blue areas represent the diffusion length estimated over the corresponding depth ranges, while the solid blue error bars indicate that these estimates are mostly representative of the diffusion length of the deepest part of section. Solid black curve represents the Johnsen model for meteorological conditions at Dome C, and black shaded area shows the sensitivity test on the mean firn temperature for the Johnsen model (Section A6).



400 4 Discussion

4.1 Evidence of post-depositional processes

Using the combination of precipitation and surface snow isotopic composition time series, together with the upper 1.5 m of firn isotopic composition, we show that there are significant difference in both mean values and patterns of variability that cannot be explained by depositional evidence both at the surface, and below the upper first centimetre. In this section, we explore how these differences can be attributed to different type of archival processes, from precipitation weighting to post-deposition.

Regarding the 6.6 ‰ difference between the precipitation and trench mean $\delta^{18}\text{O}$ values (2008-2019 period, Results section 3.3), roughly half, or +3 ‰, can be attributed to precipitation weighting alone, leaving approximately +3.5 ‰ unaccounted for. Moreover, none of the difference between surface snow and firn core can be attributed to precipitation weighting. We show that half of this remaining offset occurs between precipitation and surface snow, and the other half after the snow has been buried (Fig. 3). The VFC, which is based on the classical isotope-temperature relationship used for ice core interpretation, captures depositional processes such as precipitation weighting (Fig 3), but does not accurately represents the $\delta^{18}\text{O}$ and d-excess signals measured in surface snow and in the trench. We argue that this mismatch should be explained by the contribution of post-depositional processes, namely sublimation and solid condensation at the interface between the surface snow and the atmosphere, and metamorphism in between snow layers.

At the surface, our results support previous studies from Casado et al. (2021) and Ollivier et al. (2025b), who observed at Dome C that the surface snow isotopic composition can be modified in the absence of precipitation events, with sublimation driving an increase of $\delta^{18}\text{O}$ and a decrease of d-excess. The relative change of d-excess and $\delta^{18}\text{O}$, characterised by a slope larger than 1, is typical of sublimation and metamorphic processes (Casado et al., 2021). The strong kinetic component occurring during isotopic fractionation at sublimation and condensation during the residency phase at the surface is indeed associated with changes of isotopic composition deviating from the meteoric water line, leading to this characteristic decrease of d-excess.

Our new evidence for significant shifts in $\delta^{18}\text{O}$ occurring below the surface is a surprise compared to earlier studies. At EDML, successive trench studies showed that, apart from the first 10 to 15 cm of the firn, no significant changes of the mean isotopic composition of the snow took place during two years of snow burial (Münch et al., 2017). At depths below 15-30 cm, the temperature gradients inside the snow are relatively monotonous (Touzeau et al., 2018), which could explain why little changes were observed, especially in a period as short as two years. Here, our trench covers roughly 20 years of isotopic records, a longer period allowing isotopic exchanges can occur. This being said, it appears more likely that the most significant post-depositional processes would be driven by temperature gradients, and confined in the first 15 cm. Closer to the surface, Ollivier et al. (2025b) observed at Dome C that the difference between the surface snow (0-1 cm) and the sub-surface snow (1-4cm) ($\delta^{18}\text{O}$ values of 51 ‰ and 51.4 ‰, respectively for the period 2017-2022), was too small to be significant. They concluded that most of the post-depositional modification of the signal takes place in the upper 1 cm. Overall, the phase of the surface and sub-surface signals are almost identical, with changes in the sub surface snow isotopic composition occurring only a few days after changes at the surface (Casado et al., 2018). This feature cannot be reproduced with a simple layer stacking



model, and would imply vertical homogenization of isotopic composition through mixing or in-firm vapour exchanges. This vertical homogenization (see also Section 3.6 about mixing) could also have limited the difference between the surface and sub-surface snow, even though post-deposition is leading to an enrichment of the snow below the surface.

The occurrence of metamorphism in the upper part of the firn is further supported by measurements of snow specific surface area (SSA), an indicator of changes in snow grain size. SSA trench profiles show an average steady decrease from $45 \text{ m}^2\text{kg}^{-1}$ to $15 \text{ m}^2\text{kg}^{-1}$ down to 30 cm depth (Ooms et al., 2026), which hints to vapour transport and re-crystallization after deposition. This is consistent with measurements of the thermal skin depth of the diurnal temperature cycle, which drives metamorphism, estimated to reach 30 cm depth (Touzeau et al., 2018). These consistent lines of evidence support the facts that surface and sub-surface snow isotopic composition could homogenise over a timescale of weeks while the enrichment in heavy isotopes would continue below 4 cm depth. These processes explain why surface and subsurface snow have similar mean isotopic values while firn cores depict more enriched $\delta^{18}\text{O}$ levels.

Our findings call for the integration of post-deposition processes into ice core Proxy System Models (PSM) in order to decipher the climate signals archived in ice cores through the combined effects of deposition and post-deposition processes. We stress that the observed mean isotopic composition offset associated with the post-deposition documented here (around $+3.5 \text{ ‰}$ in $\delta^{18}\text{O}$) is significant compared to the magnitude of the mean precipitation cycle (around 10 ‰) (Dreossi et al., 2024) and EPICA Dome C glacial-interglacial ice core isotopic changes (around 8 ‰) (EPICA community members, 2004). Given the strong seasonality of today's metamorphic processes in Antarctica, and their inhibition by precipitation events (Picard et al., 2012), the magnitude of the post-deposition signal could also vary with Antarctic climate variability at inter-annual to glacial-interglacial time scales. The climatic drivers which can modulate the magnitude of these post-deposition effects, in combination with changes in climatic conditions, precipitation isotopic composition and precipitation intermittency, need to be explored and quantified to better understand their role in ice core records.

4.2 Common signal and noise contribution

We want to evaluate how much of the isotopic signal recorded in our trench stack originates from the precipitation climatic signal, and what fraction might originate from post-depositional effects and stratigraphic noise. Casado et al. (2021) had already shown that long summer periods without precipitation favour surface snow metamorphism altering the surface snow isotopic composition. While there is a positive $\delta^{18}\text{O}$ anomaly and a negative d-excess anomaly in precipitation data in 2014 (Figure 1a), the remarkable depleted d-excess trench layer identified in 2015 does not coincide with the timing of the precipitation anomaly, and cannot be attributed to the precipitation input of 2014 alone. Consistent with Casado et al. (2021), we argue that the 2015 high $\delta^{18}\text{O}$ layer does preserve a precipitation contribution, while the 2015 low d-excess layer is dominated by the signature of subsequent post-depositional processes. Casado et al. (2021) indeed showed that during the dry 2015 summer, marked by very low precipitation amounts, sublimation effects could drive a negative d-excess anomaly of -13 ‰ in surface snow, dampened by a subsequent d-excess increase due to vapour exchanges inside the firn driven by temperature gradients. This is consistent with our data showing a trench stack anomaly of -6 ‰ during the surface snow anomaly phase in summer 2015 (Figure 3c).



The trench dating uncertainty might hinder the climatic interpretation of the trench record. For instance, we cannot rule out that the enriched 2003 $\delta^{18}\text{O}$ trench is the outcome of the 2002 VFC enriched layer offset by a year (Figure 1b,d). Nevertheless, according to our VFC model, precipitation alone is not sufficient to explain the magnitude of the trench peak. We argue that the exceptionally warm summer of 2002 might have imprinted its temperature signal not only through the precipitation isotopic composition but also through fractionation during sublimation, as during summer 2014 (Casado et al., 2021). This can also explain why remarkable isotopic layers span several years, as expected from vapour exchange happening in the upper 30 cm layer representing a few years of accumulation (Touzeau et al., 2016). The period 2002-2003 is not covered by surface snow or precipitation observations, but modelling of vapour processes based on the output of reanalyses or isotope enabled Atmospheric General Circulation Models (AGCM) could provide further insight in the origin of the enriched $\delta^{18}\text{O}$ layer in the trench.

At decadal scales, the trench water isotopic composition seems to have a very low SNR, and potentially significant contributions from noise components, including precipitation intermittency, snow redistribution by wind, as well as vapour exchanges. The small common signal in the Dome C trench stack is in sharp contrast with results obtained from EDML by Münch et al. (2016) (accumulation rate $64 \text{ kg m}^{-2} \text{ yr}^{-1}$) where profiles retain a 0.5 correlation at 10-35 m distances, and a correlation based SNR of 0.9. This translates the fact that isotopic layers present in the EDML trenches are 20 cm thick seasonal layers homogeneously deposited along the transect, while in the Dome C trench the 7.5 cm annual layers are mixed and unevenly redeposited by wind on the meter-scale topography. In section 3.4, we showed the discrepancies between the observed time series of the trench stack, with its three multi-annual $\delta^{18}\text{O}$ peaks and single d-excess peak, and the simple layered virtual firn core model, with small annual $\delta^{18}\text{O}$ and d-excess peaks (Figure 3). There was no significant correlation between the stack of 26 profiles and the simulated precipitation input. In the EDML trench, by comparison, a stack of 5 cores is already sufficient to obtain a representative trench profile (Münch et al., 2016).

We have highlighted various processes that can erase traces of a common precipitation signal after deposition, namely (a) a stronger diffusion due to isotopic mixing at the surface, and (b) imprints of vapour driven fractionating processes within the firn. A spectral analysis of the diffusion length (Figure 5) reveals a smoothing of annual to multi-annual frequencies below 1.5 m depth with a diffusion length 1 to 2 cm longer than predicted by classical isotopic diffusion models. This is seemingly contradictory with the broad isotopic peaks in the trench stack inter-annual variability. Increasing the smoothing in the VFC according to these findings could broaden the peak but reduce the amplitude accordingly, making it smaller than the amplitude in the trench stack (3 ‰ in $\delta^{18}\text{O}$), and much smaller than the peaks observed in the individual profiles (horizontal standard deviation of 4.7 ‰). Therefore, we conclude that the homogeneous highly enriched layers in $\delta^{18}\text{O}$ (and depleted d-excess layer) have their origins beyond the input of precipitation.

4.3 Climatic signal recorded in Dome C firn

Since all the time series are not covering the same time periods and since the overlap is short, we can use spectral analysis to compare the signal archived in all the series without taking into account the phase of the signal, and address the question of signal variability at different time scales. Here we compare the spectra of the time series of temperature from ERA5 converted into isotopic units, the precipitation and surface snow isotopic composition, and the dated trench vertical profiles to evaluate



the impact of the different archival processes. For the trench, we include both the mean of individual profile spectra, and the spectrum of the stack (Münch and Laepple, 2018), to be able to quantify the stratigraphic contribution to the signal from the mean isotopic records. We detail all the spectral signature of the successive archival processes.

For a perfect isotopic record, the temperature signal could be approximated as a linear function that converts from temperature to isotopic units. Here, we represent this ideal target time series converting ERA5 T2m into isotopic units (grey curve in Fig. 6), and we observe the strong contribution of the seasonal cycle with peaks at frequencies of 1 year, as well as second and third harmonics, as expected for the temperature seasonal cycle in Central Antarctica (Laepple et al., 2018). In the observed isotopic content of precipitation (Figure 6, green line), the sharp annual and bi-annual peaks remain very visible, and we observe a higher power at inter-annual and decadal timescales. This can be explained by the aliasing of a cyclic signal, which tends to remove power to at the seasonal scale, and add white noise at all frequencies. This can be seen as an analogue of intermittent virtual ice cores as described in Casado et al. (2020), except that the process here does not take into account any precipitation weighting. Aliasing seen here on the precipitation time series is characterised by a narrower and better defined peak, since it does not take into account phase noise added by precipitation weighting, compared to vertical layering (Casado et al., 2020). We also know that the precipitation isotopic signal is affected by changes in air mass origins, in addition to local temperature effects, and can thus reflect inter-annual to decadal regional climate variability, for instance related to modes of variability affecting Antarctic climate. These phenomena can affect the isotopic signal and appear as non-temperature noise, or shifts in isotope-temperature relationships, and can be investigated using atmospheric general circulation models (AGCMs) equipped with water stable isotopes (Dutrievoz et al., 2025).

We expect a similar spectrum for surface snow isotopic records, because surface snow samples (1.5 cm of the top of the firn) integrate precipitation signals over the previous three to four months of precipitation events prior to the post-deposition impacts. This is confirmed by the actual spectrum (Figure 6 which further shows the reduction of the annual peak which appears broader and reduced compared to the precipitation peak, with the same higher power at inter-annual scale. The difference between the surface and precipitation spectra at the annual scale could be the visual expression of the effects of precipitation weighting, but it is surprising that this additional aliasing does not affect inter-annual power. This could be linked with the relatively short time series from which the trend is removed. We note that the effect of stratigraphic noise is not visible at this step due to the random component of the surface snow sampling, which removes the influence of spatial variability.

The mean of spectra of individual trench profiles (Figure 6, light blue) diverges from the surface spectra in two way: an order of magnitude of additional power at decadal scales (Figure 6, red arrows), and a smoothing at high frequencies leading to a significant drop of the power spectral density (Figure 6, pink arrows). Since we are considering individual vertical profiles, a significant part of the additional power at low frequencies could be linked to stratigraphic noise (Münch and Laepple, 2018). We have shown that this noisy components represent up to 65 % of the signal at decadal and higher frequencies (Section 4), represented in Figure 6 with the red arrow 'N'. The 1.2 m decorrelation length between isotopic profiles (Figure 2) indicates that the noisy component of the signal acts at a very local scale, which is that of small scale topography such as sastrugi (Picard et al., 2019). This is supported by the fact that averaging the 26 independent profiles of the trench (see Section 3.2) produces a spectrum with lower decadal scale levels (Figure 6, dark blue). Quantitatively, for the stack, this level is roughly equal to the



common signal of the 26 profiles ($C = \frac{26}{25} \cdot (S - 1/26M)$, see Section 2.4.2), suggesting that the common signal in the trench at decadal time scales still includes additional power (which we represent with the red arrow 'S'), in addition to the effect of precipitation intermittency and weighting on precipitation and surface snow spectra. This gap could be explained either by (i) the relatively low number of profiles (only 26) (Münch and Laepple, 2018), (ii) residual stratigraphic noise characterised by a decorrelation length larger than 50 meters, or (iii) post-deposition influence at inter-annual scale (Figure 6, red arrow 'b'). We note that the spectral powers of the core stack are comparable to those in the levelled trench (Fig. S2 b), so that this gap is not a result of gain of mean power upon alignment.

In section 3.6, we have shown that the smoothing effect is stronger than predicted by the Johnsen diffusion model, and could be caused by temperature gradient metamorphism and mechanical mixing. This mixing could be linked to mechanical mixing from wind redistribution, as well as through metamorphic mixing through fast vapour exchange in the interstitial air associated with the enhanced and daily varying temperature gradients near the surface (Touzeau et al., 2018; Casado et al., 2021).

To confirm these hypotheses, future studies could combine outputs from an isotope enabled GCM and virtual firn core model including vapour exchanges to quantify the contributions of each process at play during snow archival, and their sensitivity to climate conditions. The comprehensive set of isotopic data available at Dome C, including our new trench datasets, demonstrates the need to account for these processes, and in particular post-depositional processes, into our current understanding of the archiving of the isotopic signal in ice core records. Expanding observational datasets over longer time scales beyond 20 years could also improve the documentation of the magnitude of noise added at inter-annual and decadal scales due to precipitation weighting and stratigraphic perturbations.

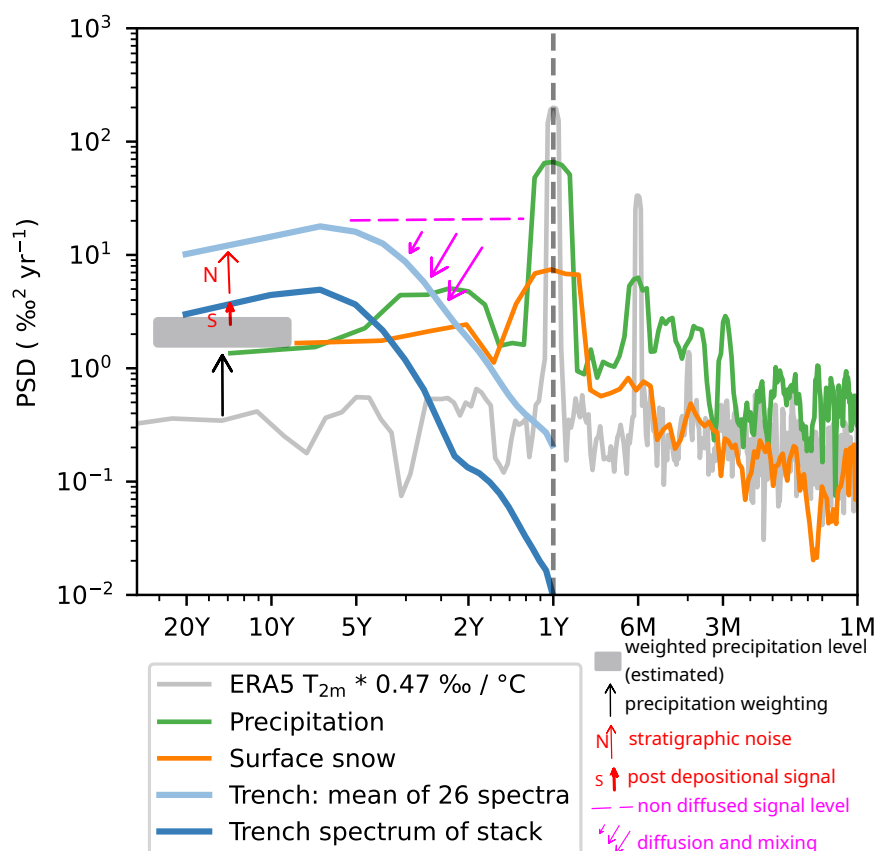


Figure 6. Power spectra of the three observational datasets of snow isotopic composition; precipitation (green), surface snow (orange) and trench, including the mean of trench profile spectra (light blue), and the spectrum of the mean (dark blue). At decadal scales, the mean trench spectra is 30 times higher than the initial temperature signal (grey). The intermediate weighted precipitation level (greyed area, see main text) separates this gap between the effect of precipitation weighting (black arrow) and stratigraphic noise (red arrow 'N'). Taking the spectrum of the mean trench profile (dark blue) removes most of the stratigraphic noise effect, with a possible residual global post-depositional signal (red arrow 'S').



5 Conclusions

555 We used an extensive dataset of 39 simultaneous high resolution 1.5 m deep snow profiles to study the stable water isotopic composition of near-surface firn at Dome C, in the centre of the East Antarctic plateau. These snow pits cover 20 years of snow accumulation (2000-2019) and were previously aligned and dated using chemistry data, independently of isotope measurements. This period overlaps with continuous weekly precipitation and surface snow sampling ongoing since 2008 and 2014, respectively. These three datasets have been compared to monitor the evolution of isotopic composition of snow during the archival process. Additionally, we used a simple virtual firn core model based on daily surface air temperature and precipitation outputs of the ERA5 reanalysis to compare the trench records with an idealised precipitation layering interpretation of ice cores records. Our analyses provide several lines of evidence for post depositional modification of the isotopic content of snow along the surface and subsurface archival processes. These new lines of evidence confirm earlier findings suggesting that the inter-annual isotope signal in Dome C firn is dominated by noise and post-depositional processes with limited climatic information content (Casado et al., 2021; Ollivier et al., 2025b; Wahl et al., 2022).

The mean values show a post-depositional enrichment of snow of nearly +7 ‰ in $\delta^{18}\text{O}$ compared to the precipitation time series for the period 2014-2019, with a +5 ‰ increase from precipitation to surface snow mean values, and an additional +2 ‰ from surface snow to trench mean values. Similarly, d-excess shows a -5 ‰ depletion from precipitation to surface snow, and an additional -0.7 ‰ from surface snow to trench mean values. These differences are higher than the +3 ‰ (resp. -2.5 ‰) enrichment in $\delta^{18}\text{O}$ (resp. depletion in d-excess) expected from precipitation weighting alone. This indicates the occurrence of post-deposition modification of the isotopic composition in the firn beyond surface residency. The vertical variability of individual snow profiles reveal smoothing of the near surface signal stronger than predicted by the classical firn isotopic diffusion model (Johnsen et al., 2000), and multi-annual variability of the mean profile that cannot be accounted for by a simple precipitation layering model. Three exceptionally enriched $\delta^{18}\text{O}$ and one depleted d-excess layers can be identified across the trench, with a deposition time estimate coherent with previously documented events associated with post-depositional fractionation. One enriched $\delta^{18}\text{O}$ layer could be explained by the remaining signal of a high temperature signal in precipitation $\delta^{18}\text{O}$ with subsequent post-deposition effects. The remarkably low d-excess layer in 2015 is consistent with dry summer conditions driving large negative d-excess anomalies through sublimation. These findings suggest a discernible fingerprint of exceptional sublimation-prone meteorological conditions in Dome C ice cores.

580 Besides these few horizontally coherent layers, the isotopic signals are characterised by a high spatial variability, with a decorrelation length of about 1.2 m and inter-profile correlation coefficient at decameter scale as low as 0.2. The signal analysis on a subset stack of 26 evenly distributed profiles 2 m apart reveals individual profiles with 65 % to 80 % of noise at decadal to multi-annual timescales. Our careful high resolution alignment based on chemistry increased the SNR by up to 50 % compared to a simple stacking of trench profiles based on depth, confirming that the noise is linked to the deposition of snow at different depths levels due to variable meter-scale topography at the surface. Contrary to studies carried out at sites with higher accumulation rates such as EDML (Münch et al., 2016), the comparison of the mean trench signal with the signal expected only from the temperature-isotope precipitation input shows no significant correlation between the time series. This suggests



that there could be a threshold ratio between the competing effects of snow accumulation and mixing, separating locations such as EDML where the snowpack can build up coherent snow layers, and Dome C where annual precipitation layers are smoothed out and super-imposed by post-depositional isotopic signal. This suggests that the interpretation of decadal variations from ice core isotopic records should account for different driving processes for such different sites. Past climate reconstructions would thus need to account for the respective effects of precipitation as well as post-depositional processes. While earlier studies have supported past precipitation-weighted temperature reconstructions dominated by deposition processes, our study suggests the possibility for sublimation-imprinted archival processes, amplified in the absence of summer precipitation events. Not only would this be important to push climate reconstructions based on Dome C ice cores to their high-frequency limit, but also to strengthen the understanding of the role of post-deposition changes under different climatic conditions, for instance during contrasted glacial and inter-glacial conditions, with different contributions of temperature, moisture transport and wind effects on post-depositional processes. The development of proxy models simulating post-deposition effects is therefore needed to bridge the gap between the evidence of the importance of these processes from available present-day datasets and climatic reconstructions at various time-scales.

Data availability. The isotopic trench data will be made publicly available on Pangaea (<https://www.pangaea.de/>) upon publication.



Appendix A

A1 Isotopes in precipitation and temperature

We have applied an exclusion criteria for precipitation samples that are believed to be affected by sublimation, based on d-excess values (main text section 2.3). For transparency, we illustrate the effect of the d-excess exclusion criteria on the precipitation time series compared to the fitted ERA5 temperature (Figure A1), and on the spectra (Figure A2). Here we see that using the full dataset produces a spectra above that of surface snow, which is counter intuitive since surface snow roughly corresponds to 2-monthly weighted precipitation, which should be above the precipitation spectrum at decadal scales (Supplement S2). We interpret this as the precipitation time series exhibiting more variability due to samples being affected by sublimation on the collecting table. Restricting the precipitation dataset with the criteria on d-excess yields a more consistent picture.

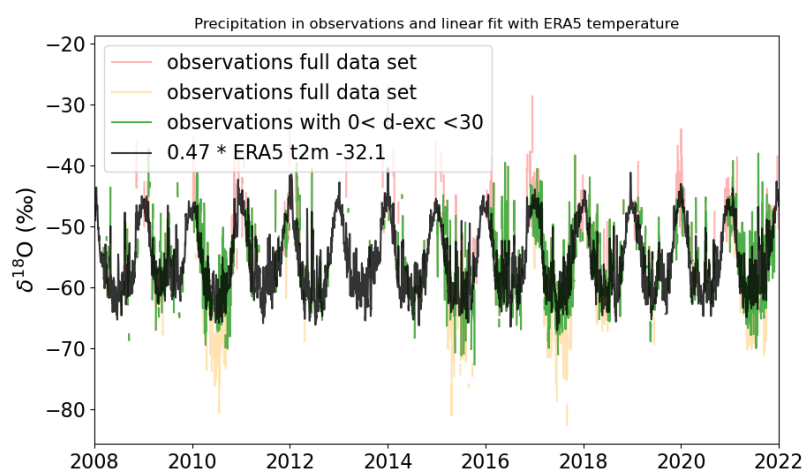


Figure A1. The precipitation dataset (orange and red line) is restricted by applying the criteria for d-excess (green line). Its amplitude is then more comparable to that of the ERA5 temperature time series fitted on the precipitation isotopic composition (black line).

A2 Firn temperature

For the main text we have used the seasonal cycle of firn temperature as modelled by Laepple et al. (2018) to compute the Johnsen diffusion length (Equation 3). Here we compare this seasonal cycle of temperature against more recently available time series of surface temperature of Ollivier et al. (2025a) and of the British Surface Radiation Network (BSRN) Concordia station (Lupi et al., 2021) (Figure A3). We present our results regarding diffusion length in the main text with a sensitivity test of ± 2 K around the temperature of Laepple et al. (2018) to account for potentially higher average or maximum summer

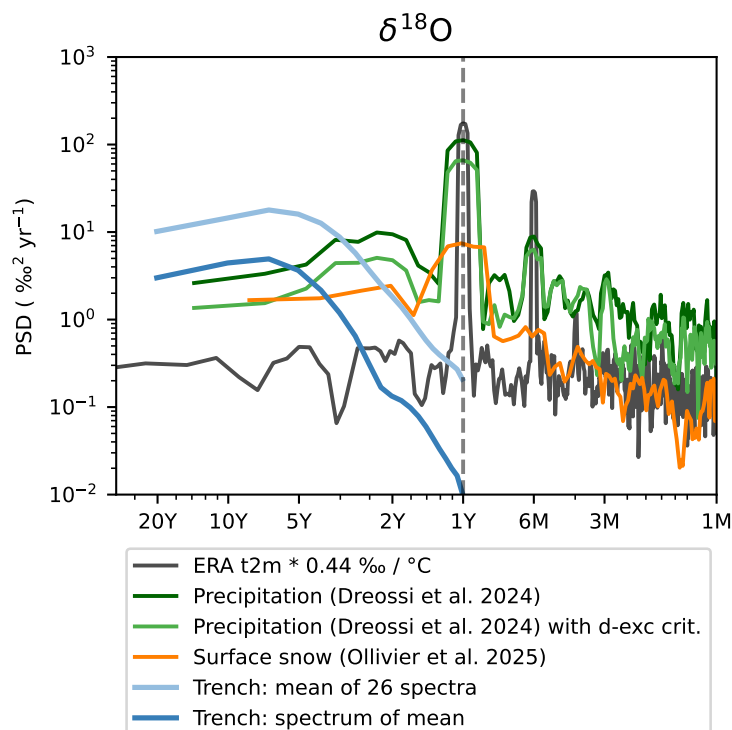


Figure A2. We replicate Figure 6 from the main text with the additional curve of the raw precipitation spectrum. In the method (Section 2.3, we explain why we exclude a certain fraction of data points in the precipitation isotopic composition time series, as we suspect it could have been subjected to fractionation on the collection table.

temperatures. Despite this uncertainty in the input temperature for the Johnsen model, other mechanisms should be involved to account for the observed diffusion length in the trench (See figure 5 in the main text).

620 A3 Aligned and levelled trench

In figure A4, we provide the 2D view of the aligned and levelled configurations of the trench site by side. The common signal in horizontal averages of these profiles are compared in section 3.2 (decorrelation length) and 3.5 (signal to noise ratio).

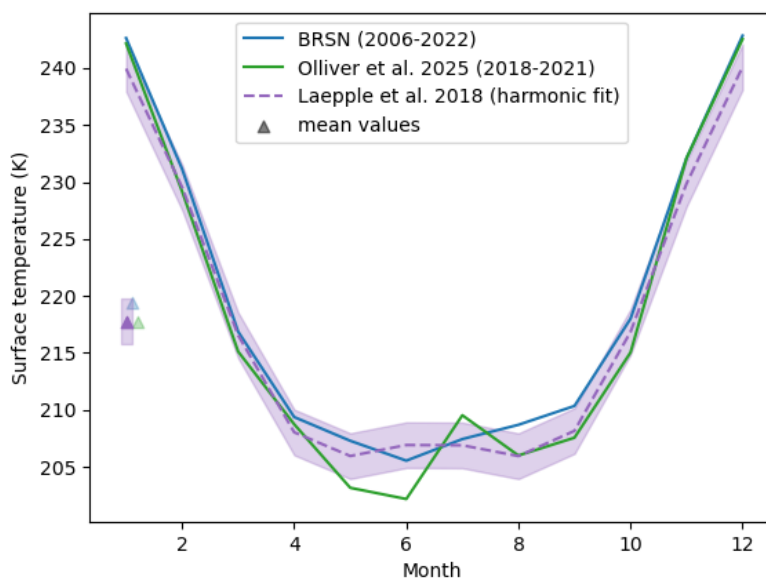


Figure A3. Seasonal averages of surface temperature reconstructed by Ollivier et al. (2025a), and of the Dome C station of the Baseline Surface Radiation Network Lupi et al. (2021) compared against the modelled time series (Equation 3) in the main text.

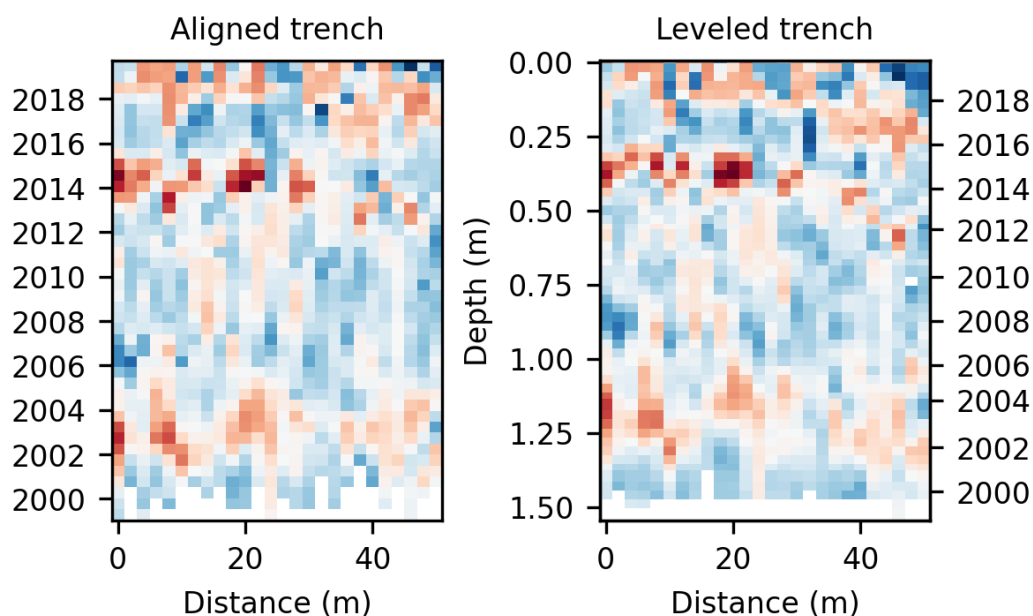


Figure A4. The 26 profiles evenly distributed at 2 m in the aligned and levelled configuration of the trench.



A4 Mean values

In the main text (Figure 3b,d), we focused on the overlapping period 2014-2020 of the three observational datasets to describe differences in average values. Here we provide more estimates based on other periods of interest. We also provide more detail on the calculation of the $+3\text{‰}$ offset in $\delta^{18}\text{O}$ and -2.5‰ offset in d-excess attributed to precipitation weighting, as well as the comparison of the precipitation weighting effect in firn cores and surface snow ($+0.2\text{‰}$ in $\delta^{18}\text{O}$).

To estimate the effect of precipitation weighting, we follow Ollivier et al. (2025b) and calculate mean values of weighted precipitation estimates for the periods 2008-2010 (Table A1a, g) and 2017-2019 (Table A1b,h) where they are available. We repeat this estimation using mean values in precipitation, surface snow and firn core of the VFC model (Section 2.4.1), over the same period as the trench (1999-2019) (Table A1f,l).

The differences between the trench isotopic composition and the average of the precipitation time series over the overlapping period, from 2008 to 2019 (Table A1c, i) is $+6.8\text{‰}$ and -5.8‰ for $\delta^{18}\text{O}$ and d-excess, respectively (statistically significant, Kruskal-Wallis, p-value < 0.05). This is very close to the $+7.1\text{‰}$ for $\delta^{18}\text{O}$ and -6‰ for d-excess found for 2014-2020.

The average value of $\delta^{18}\text{O}$ in weighted precipitation indicate a $+3.6\text{‰}$ (2008-2010) or $+2.1\text{‰}$ (2017-2019) offset compared to the arithmetic mean of the time series. For d-excess, the differences for the two periods are -3.1‰ and -1.9‰ , respectively. Ollivier et al. (2025b) reported similar values for the period 2017-2021, showing that the mean value of $\delta^{18}\text{O}$ (resp. d-excess) in weighted precipitation is $+2.8\text{‰}$ higher (resp. -3.0‰ lower) than the arithmetic mean.

We further use the VFC to evaluate precipitation weighting effect in surface snow (Table A1f,l). The time series of the top 1 cm of the VFC for 1999-2019 indicates a change of $+0.2\text{‰}$ in $\delta^{18}\text{O}$ and -0.2‰ in d-excess from the VSS to the VFC.

Finally, we stress the fact that $\delta^{18}\text{O}_{\text{T2m}}$ and d-excess_{T2m} correctly represent mean values in precipitation, despite the average values of the time series being slightly different (Figure 3b,d, green and black stars). The mean $\delta^{18}\text{O}_{\text{T2m}}$ is $-55.6 \pm 0.1\text{‰}$ (14.8 ± 0.1 for d-excess_{T2m}). This average value is representative of mean daily temperatures, without the effect of precipitation intermittency, i.e. also considering days without precipitation. On the other hand, the average values during the days of precipitation sampling (within the period 2008-2019) are -56.3 ± 0.1 (15.4 ± 0.1 for d-excess) (Table A1f,l, bracketed values), which are within 0.2‰ of the observed means (Table A1d,j).

A5 VFC experiment with surface snow

In section 3.4, we compared the variability of surface snow observations with the virtual surface snow (VSS) constructed from the upper 1 cm of the VFC at daily time steps. In Figure A5, complementary to Figure 3, we show the VSS alongside surface snow observations.



Table A1. Mean isotopic composition of the precipitation, surface snow and trench datasets over their respective sampling periods. Periods where precipitation amounts are available are also shown (2008-2010, columns a, g and 2017-2019, columns b,h). Periods extend from the beginning of the starting year to the end of the finishing year. The (*) symbol indicates that we have ignored precipitation samples with d-excess values outside of the range 0 to 30 ‰ (Section 2.3) . The 3 datasets overlap in 2014-2019 (columns d,j). For periods 2008-2010 and 2017-2019 where measured precipitation amounts are available, we give the weighted isotopic composition in precipitation. For the other periods, we give an estimate in brackets based on ERA5 precipitation amounts. The last columns (f,l) shows the result of the VFC experiment, with input precipitation based on a linear fit with temperature and isotopic composition of precipitation for the period 2008-2019 (Equation 1), the virtual surface snow time series and the virtual firn core. Surrogate precipitation has daily values for precipitation isotopic composition, so even days without precipitation contribute to the mean. {□} indicates mean value of the surrogate series for the precipitation sampling dates for 2008-2019.

$\delta^{18}\text{O}$	Observations					VFC model
	(a)	(b)	(c)	(d)	(e)	(f)
	2008-2010	2017-2019	2008-2019	2014-2019	1999-2019	1999-2019
Precipitation*	-56.9 ± 0.3	-56.6 ± 0.3	-56.3 ± 0.2	-56.3 ± 0.2		-55.6 ± 0.1 { -56.3 ± 0.1 }
Weighted precipitation*	-53.3 ± 1.0	-54.5 ± 1.0				-52.6 ± 0.1
Surface snow		-51.7 ± 0.2		-51.4 ± 0.1		-52.8 ± 0.1
Trench / firn core	-50.5 ± 0.5	-49.0 ± 0.8	-49.5 ± 0.4	-49.2 ± 0.6	-49.7 ± 0.3	-52.6 ± 0.1

d-excess	Observations					VFC model
	(g)	(h)	(i)	(j)	(k)	(l)
	2008-2010	2017-2019	2008-2019	2014-2019	1999-2019	1999-2019
Precipitation*	16.2 ± 0.4	16.1 ± 0.3	15.3 ± 0.2	15.2 ± 0.3		14.8 ± 0.1 { 15.4 ± 0.1 }
Weighted precipitation*	13.1 ± 0.1	14.2 ± 1.0	(13.7 ± 1.0)	(14.2 ± 1.0)		12.5 ± 0.1
Surface snow		11.1 ± 0.2		10 ± 0.2		12.7 ± 0.1
Trench / firn core	10.9 ± 0.7	9.6 ± 0.8	9.5 ± 0.5	9.2 ± 0.7	9.9 ± 0.3	12.5 ± 0.1

A6 Estimation of diffusion length

In the Methods, section 2.4.3, we present an estimation of diffusion length in smoothed time series by fitting the power spectrum of the series at high frequencies with a linear slope associated with convolution with a gaussian kernel. Here, we show (1) that this method presents a bias by applying it to time series diffused with a known diffusion length, (2) that this method is not limited by the coarse 3 cm resolution of the trench and (3) that the method is robust relative to the frequency range used for the linear fit.

First, we apply the computation to white noise virtual cores diffused with a known Johnsen model and sampled at 3 cm resolution, and compare the expected diffusion length with that computed with equation 10. We repeat the experiment 100 times and give the 95 % confidence interval on the diffusion length estimate.

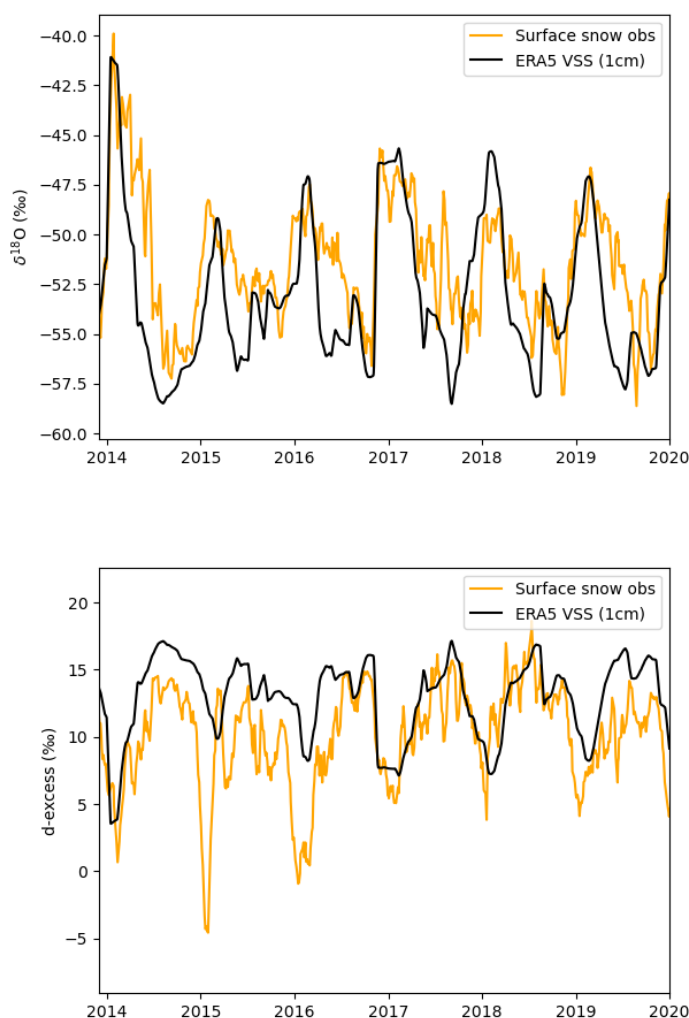


Figure A5. Surface snow observations (orange) with the output of the VSS experiment (black) for the periods 2014–2020. This is a complementary figure to Fig. 3, and the black horizontal line markers in Fig. 3b,d are the average values of the VSS time series shown here.

This sensitivity tests shows a slight over-estimating bias compared to the mean of the original diffusion profile over the depth range (Figure 5, green dashed line), and appear to represent the diffusion length in the deeper section of each depth range where it is most intense. Still, the observed diffusion length in the trench is above this measurement bias, confirming a higher diffusion length in near surface firn than that predicted by the Johnsen model.



665 Second, we have found no difference between diffusion length values estimated on 3 cm resolution profiles or on the eight
finer 1.5 cm resolution profiles (Figure A7). This shows that a 3 cm resolution is fine enough to perform this analysis on the
trench data. Similarly, the diffusion length for the Johnsen model calculated on finer white noise profiles (1 mm resolution) is
the same as that calculated from the 3 cm resolution profiles (Figure A6).

670 Lastly, since the diffusion length in the upper 1.5 m of the snowpack is found to be in the range 0-6 cm, one can wonder
whether the fit in the 6 to 9 m^{-1} frequency range is accurate to estimate it. It turns out to be the case, since the gaussian filter
affects values up to $\pm 5\sigma$, so the power spectrum of frequencies down to 15 cm will be affected by diffusion. In our calculation,
we have fitted the diffusion length in the range 6 to 9 m^{-1} , corresponding to periods of 11 cm to 15 cm. Different ranges have
been considered (6 to 13 m^{-1}); the resulting diffusion length showed little variations, with a standard deviation less than 5 %
of the reported values, which is less than the deviation between profiles.

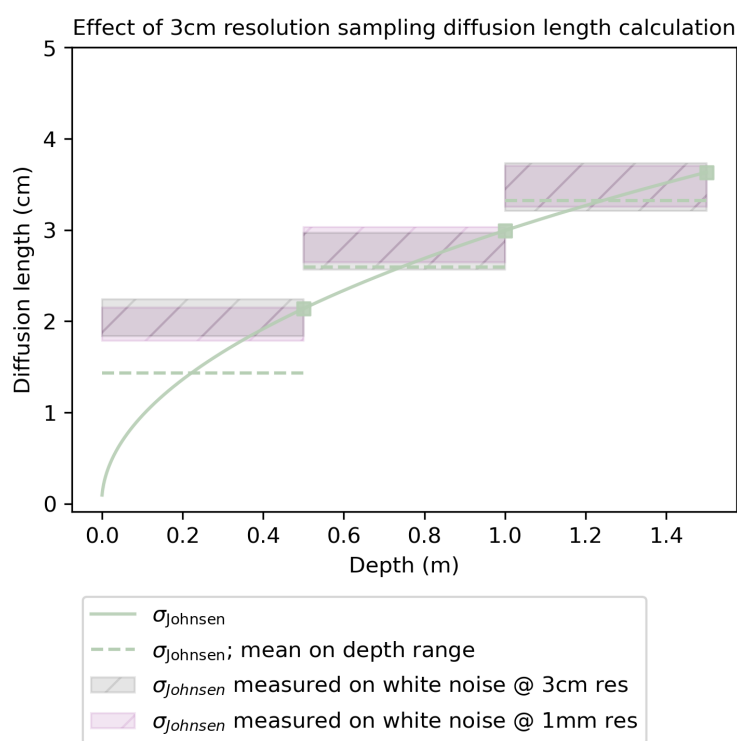


Figure A6. Sensitivity test on the diffusion length estimation method, by applying the method to white noise at 3 cm resolution (dashed green areas) and 1 mm resolution (dashed purple area) diffused with a known diffusion length given by the Johnsen model (solid green line). The result is slightly biased compared to the arithmetic mean over the depth range considered (dash green lines) but accurately represents the maximum value over the depth range (green square).

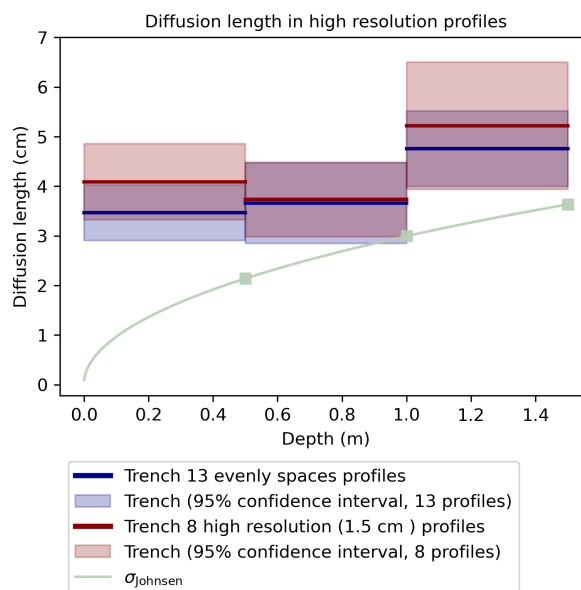


Figure A7. Sensitivity test on the influence of resolution on the estimation of the diffusion length. We compare the diffusion estimated from the trench stack of the main text (26 profiles) with mostly 3 cm resolution profiles (blue), and the stack of 8 high resolution (1.5 cm) profiles (red). Both are 2-3 cm above the diffusion length predicted by Johnsen (green line).

675 *Author contributions.* Contributor Roles Taxonomy (CRediT) author statement; **All authors:** Writing - Review & Editing. **AO:** Conceptualization, Formal analysis, Visualization, Data curation, Writing - Original draft preparation, Validation. **MC:** Project Administration, Funding acquisition, Conceptualization, Visualization, Data curation, Writing - Original draft preparation, Validation, Resources. **SW:** Writing - Original draft preparation. **AZ:** Ressources, Data curation. **PA:** Resources. **GP:** Resources. **LA:** Resources. **VMD:** Conceptualization, Supervision. Ressources: MC, GP, LA and PA participated in field work. AZ performed the isotopic measurements for the trench data.

680 *Competing interests.* At least one of the (co-)authors is a member of the editorial board of Climate of the Past.

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