Are there multiple scaling regimes in Holocene temperature records?

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Abstract

The concept of multiple scaling regimes in temperature time series is examined, with emphasis on the question whether or not a mono-scaling model can be rejected from the data at hand. A model with only one regime is simpler and is preferred if this explains the observed variability. Our analysis of spectra from reconstructed air temperature from Greenland and Antarctica ice cores shows that a scale break around centennial time scales is evident for the last glacial period, but not for the Holocene. Nor by analysing a number of late Holocene multiproxy temperature reconstructions can a significant scale break be identified. Our results indicate that a mono-scaling model cannot be rejected as a null model for the Holocene climate up to at least millennial time scales, although it can be rejected for the glacial climate state. The scale break observed from the glacial time ice core records is likely caused by the influence of Dansgaard–Oeschger events and teleconnections to the Southern Hemisphere on centennial time scales. From our analysis we conclude that the two-regime model is not sufficiently justified for the Holocene to be used for temperature prediction on centennial time scales.

1 Introduction

The main focus of this paper is the scaling properties in paleotemperature records at centennial and millenial time scales. In particular we study the differences in variability between glacial/interglacial time periods, and we discuss the justification of separating temperature variability on different time scales into distinct scaling regimes. The notion of “scaling” in climatic time series is based on the observation that the natural variability of the Earth’s surface temperature can be modelled as a persistent stochastic process, with superposed trends and quasi-periodic modes representing variability which is not included in the noise background. There is a considerable body of literature suggesting that long-range memory (LRM) stochastic processes are good statistical models for
de-seasonalised local and global temperature records on time scales from months up to a century or more (Koscielny-Bunde et al., 1996; Rybski et al., 2006; Efstathiou et al., 2011; Rypdal. et al., 2013; Østvand et al., 2014). The standard continuous-time stochastic LRM processes are the fractional Gaussian noise (fGn) and fractional Brownian motion (fBm). The latter is the cumulative integral of the former, and both are said to be scale-invariant (or scaling). The strength of persistence, or memory, in an LRM stochastic process is described by the spectral exponent $\beta$; the power spectral density takes a power-law form $S(f) \sim f^{-\beta}$. The fGn has $-1 < \beta < 1$ and stationary variance, while the fBm has $1 < \beta < 3$ and a non-stationary variance that grows in time like $\sigma(t) \sim t^{\beta-1}$. The fGn is persistent (exhibits long-range memory) if $\beta > 0$, and is anti-persistent if $\beta < 0$.

According to the glossary of Kantelhardt (2011) a scaling regime can be identified only if a power law is valid for scales spanning at least one order of magnitude, be it frequency or time scale. The term “break in scaling” will in this paper mean that there exists more than one scaling regime in a single time series, where each regime complies with Kantelhardt’s definition and is valid for at least one order of magnitude. “Deviation from scaling” will be synonymous with violation of Kantelhardt’s definition.

Ditlevsen et al. (1996) analysed the scaling in high-resolution ice core data from Greenland. Two different overlapping time series were used to create a composite power spectrum, and from this a break in scaling was identified around centennial time scales. A white noise ($\beta = 0$) was identified for time scales shorter than centennial, while on longer time scales a non-stationary regime with $\beta \approx 1.6$ was found. One of the time series covers 0–91 kyr BP, and the other 0–3 kyr BP. This procedure of combining different time series into one power spectrum is problematic since the two time series reflect different climate states with different variability. The longer time series is dominated by the glacial state, while the short one contains only Holocene data. The different variability of the two states is seen clearly by direct inspection of the data, e.g., from comparing the Holocene part of the GRIP ice core (Fig. 4a) and the last glacial period from the same ice core (Fig. 6a, c).
time series is less than half of the glacial one, and the latter looks more bursty. The records in Fig. 4a and Fig. 6a, c can be associated with different stochastic processes. The Holocene record is similar to an fGn with low persistence, while the records from the last glacial period are strongly persistent (even non-stationary), and exhibits strong intermittency.

Pelletier (1998) estimated the power spectra and scaling exponents from a deuterium record from the Vostok ice core as well as from instrumental local data, and also created composite spectra from the records. Huybers and Curry (2006) and Lovejoy and Schertzer (2012) have studied the scaling in multiple proxy data sets covering time scales from years to millions of years. Both papers report a break in scaling from a stationary process ($\beta < 1$) to a non-stationary process ($\beta > 1$) on a transition time scale $\tau_c \sim 10^2$ yr. The break in scaling is seen from composite spectra of paleotemperature records based on different proxies and reconstruction techniques, where many of the records span hundreds of kyr. Since glaciation is the dominating climate state in the Pleistocene, the spectra obtained in those papers are typical for glacial climate. Huybers and Curry (2006) suggest that the power-law continuum in the spectrum of surface temperature on time scales between one year and a century is a result of an inverse cascade in frequency space driven by the seasonal cycle forcing. The non-stationary scaling regime from century time scale and longer is proposed to be the result of a nonlinear response to the Milankovitch cycle forcing. From the composite spectra, they infer scaling exponents in the range $\beta = 0.37–0.56$ for time scales $\tau < 10^2$ yr, and $\beta = 1.29–1.64$ at longer time scales. Lovejoy and Schertzer (2012) introduce three different scaling regimes: the “weather” regime ($\beta \approx 2$ for time scales up to 10 days), the “macroweather” regime ($\beta \approx 0.2$ for time scales from 10 days to $10^2$ yr), and the “climate” regime ($\beta \approx 1.4$ for time scales from $10^2$ yr and longer).

Other results reported in the literature support our hypothesis of different scaling in glacial and interglacial climate, with the scale break at centennial time scales absent for the Holocene. Blender et al. (2006) analysed the scaling properties of a 10 kyr long general circulation model (GCM) climate simulation, and no scale break can be de-
tected at centennial time scales. Lovejoy et al. (2013) make similar observations and conclude that GCM’s do not predict climate, only macroweather. Roe and Steig (2004) found by using a short-range memory AR model that the characteristic time scales for paleotemperature ice core records were significantly shorter during the Holocene than during the last glacial period. This study is important for our reasoning, but the idea needs to be adapted to a long-memory model. We will separate the ice core records into glacial and interglacial time series and demonstrate the fundamentally different scaling properties of these climate states, and we will analyse other temperature reconstructions for the Holocene in search for a detectable scale break.

The methodology applied in our study is not standard, because we encounter problems when dealing with unevenly sampled data. We can either interpolate to obtain even temporal spacing, or we can use a method developed specifically to analyse unevenly sampled data. We choose to do the latter by applying the Lomb–Scargle periodogram (LSP), because interpolation acts as a low-pass filter in the part of the time series with the larger sampling intervals.

The paper is organized as follows: in Sect. 2 we address the issues of uncertainties and limitations of proxy-based reconstructions, and the implications for the existence of separate scaling regimes are discussed. Section 3 describes the LSP method, and information about the model and the data used can be found in Sect. 4. The results from the analysis are presented in Sect. 5, and discussion and conclusion follow in Sect. 6.

2 The concept of multiple scaling regimes in the Holocene

Lovejoy and Schertzer (2012) identify two scaling regimes in a number of Holocene temperature records. In instrumental data the transition time $\tau_c$ is found to be $10–30$ yr, in proxy/multiproxy reconstructions it is $40–100$ yr, while for one of the ice core paleotemperature records it is approximately $2000$ yr. Hence, it seems difficult to identify a universal $\tau_c$ from the data examined in that paper. For the proxy/multiproxy re-
constructions that were analysed in Lovejoy and Schertzer (2012), the time period 1500–1979 was selected because it was common to all reconstructions, and the medieval warm period was avoided. However, by starting in the Little Ice Age the series are strongly influenced by steadily increasing solar, as well as anthropogenic, forcing. A pronounced linear trend has strong effect on the estimate of the scaling exponent from power spectra unless the time series is linearly detrended. This is also the case for the Haar fluctuation analysis, which was also applied in Lovejoy and Schertzer (2012).

Scaling analysis using composite spectra based instrumental or proxy data sets is problematic for several reasons. The various data sets are representative for different degree of spatial averaging and different local dynamics forming the proxies, and this will also affect the estimates of the scaling exponent. The instrumental data are global averages, while proxy/multiproxy time series represent regional or at best hemispheric temperature, where continental data are more abundant than marine due to accessibility. The ice core data represent a special type of regional continental temperature, originating from an area covered by snow and ice throughout the year. For these reasons we avoid in this study to study composite spectra based on different reconstructions spanning different time scales and climatic states, and performed by different research groups.

The techniques used to estimate the scaling exponent have inherently higher uncertainties on the longest time scales, due to sparse data on these time scales. A rule of thumb is that the scaling properties for a time series of length $N$ should be estimated only up to time scales $N/4$, since the uncertainty on time scales longer (frequencies lower) than this is too large to make meaningful estimates. Suppose, for instance, we want to establish that we have scaling in annual data on scales up to 100 yr. Then we need a series which is 400 yr long. If we want to establish the existence of a different scaling regime on time scales longer than 100 yr for a time series, we need to know with reasonable certainty the spectral estimates up to one millenium. As we will demonstrate in Sect. 5, this implies that we need record lengths spanning several millennia to
bring the uncertainty of $\beta$ below the limit needed to reject the mono-scaling hypothesis. More generally, we need a record length of the order of $10^2$ times the smallest time scale of a scaling regime.

Instrumental temperature data are not included in our analysis because previous studies do not show pronounced breaks in the scaling after detrending to account for influences from anthropogenic warming (Rypdal. et al., 2013). Detection of scaling properties in regional or hemispheric proxy/multiproxy temperature time series is possible but not optimal, since these records generally cover the past 2000 years or less, and, even though they usually are given with annual resolution, some are effectively filtered to vary smoothly on annual time scale, and have effective resolution from 5 to 10 yr. For some of the available proxy/multiproxy reconstructions an enhanced power can be inferred relative to a mono-scaling spectrum on time scales longer than a century, but data are too sparse to show that this enhanced power represents a new scaling regime.

The deep ice cores sampled at Greenland and in Antarctica provide the most suitable data sets for studying possible scale breaks in both the Holocene and the last glacial period, due to the high temporal resolution and long duration. It can be argued that the Holocene part of the Greenland ice cores GRIP, NGRIP and GISP2 is exceptionally stable compared to other proxy reconstructions of Greenland and North-Atlantic climate, but similar stability is seen also for the Antarctic ice cores EPICA, Vostok and Taylor dome. When comparing the Holocene ice core records with reconstructions from other regions and based on other proxies, one needs to keep in mind that local variability and the sensitivity of the various proxies to temperature changes makes each reconstruction unique.
3 Methods

3.1 Estimation of power spectral density

The periodogram is applied as an estimator for power spectral density (PSD) for evenly sampled time series of length $N$. It is defined here in terms of the discrete Fourier transform $H_m$ as $S(f_m) = (2/N)|H_m|^2$, $m = 1, 2, \ldots, N/2$. The sampling time is the time unit, and the frequency is measured in cycles per time unit: $f_m = m/N$. $\Delta f = 1/N$ is the frequency resolution and the smallest frequency which can be represented in the spectrum, while $f_{N/2} = 1/2$ is the Nyquist frequency (the highest frequency that can be resolved). The periodogram has a poor signal to noise ratio, but since we are interested in studying the overall shape (scaling) of the spectrum, and not the power at specific spectral peaks this is not a problem here. By presenting the periodogram in a log-log plot, the scaling exponent $\beta$ can be estimated by a linear fit to the power spectrum; $\log S(f) = -\beta \log f + c$. In the present study the periodogram is log-binned before fitting to ensure that all time scales are weighted equally (Østvand et al., 2014).

We also apply a version of the periodogram known as the Lomb–Scargle periodogram (LSP), which does not require the time series to be evenly sampled (Lomb, 1976; Scargle, 1982). While the standard periodogram is based on Fourier analysis (Schuster, 1898), the LSP is based on a least-squares fit of sinusoids to the data. We use the R package `lomb`, and the power is normalized by multiplying by $\sigma^2/N$, where $\sigma^2$ is the variance. For time series of $N$ data points $Y_j = Y(t_j)$ collected at times $t_j$ where $j = 1, 2, \ldots, N$, with mean value $\overline{Y}$, the Lomb–Scargle periodogram is defined as,

$$S_N(\omega) = \frac{1}{2\sigma^2} \left\{ \frac{\left[ \sum_j (Y_j - \overline{Y}) \cos \omega(t_j - \tau) \right]^2}{\sum_j \cos^2 \omega(t_j - \tau)} + \frac{\left[ \sum_j (Y_j - \overline{Y}) \sin \omega(t_j - \tau) \right]^2}{\sum_j \sin^2 \omega(t_j - \tau)} \right\}, \quad (1)$$
3.2 Test of the Lomb–Scargle periodogram

The LSP was originally designed to detect a periodic signal hidden in noise, and has been applied to periodic data with random missing values such as astronomical observations (Lomb, 1976; Scargle, 1982), biological rhythms (Ruf, 1999; Van Dongen et al., 1999), and heart-rate signals (Laguna et al., 1998). In the proxy-based climatic time series we don’t expect perfect periodicities and data points are not randomly missing. The sampling interval rather increases systematically as one goes backward in time. It is therefore not a priori obvious that this method can give confident estimates of the scaling exponent for the ice core time series. Pelletier (1998) used the Lomb periodogram to estimate the scaling exponent, but did not discuss the sensitivity of the method. We perform such a test on ensembles of synthetic fGn’s and fBm’s, respectively. For each realization in the ensemble, the scaling exponent is estimated from the LSP. The mean exponent value as well as the error based on the 2.5 and 97.5% quantiles are estimated. The LSP gives the same results as the ordinary periodogram when the sampling is even. The next step in the test is to remove data points from the synthetic data sets and repeat the calculations for each realization. Data is removed in such a manner that the sampling intervals become identical to those we find in ice core data. We have chosen a section of the low-resolution GRIP $\delta^{18}$O time series covering the Holocene, and another one from the last glacial period as the basis for this test (see Sect. 4 for data description). The test is carried out by first generating synthetic data sets where the time step is chosen to be the least time step in the observed record. The synthetic time series is then interpolated, and we sample this interpolation function at the times known from the ice core time series. The “resampled” time series

$$\tau = \left(\frac{1}{2\omega}\right)\tan^{-1}\left[\frac{\sum_j \sin 2\omega t_j}{\sum_j \cos 2\omega t_j}\right]$$

(2)
has the same number of data points as the GRIP Holocene/last glacial period time series, and \( \beta \) is estimated in the range \( \frac{1}{20} - \frac{1}{333} \) yr\(^{-1} \) for the Holocene, and \( \frac{1}{200} - \frac{1}{3333} \) yr\(^{-1} \) for the last glacial period. Figure 1 shows the result when synthetic data are sampled like the low-resolution GRIP Holocene (Fig. 1a) and low-resolution GRIP last glacial period (Fig. 1b). Because the least time step between values is different in the GRIP Holocene and last glacial period, the length of the synthetic data sets are also different. This leads to different error bars for the estimates. From Fig. 1 we observe that the estimated \( \beta \) is close to the true \( \beta \), except for true \( \beta \) slightly greater than unity. Bias and errors are similar to the standard periodogram and shows that the LSP is a very useful substitution for the periodogram for these data records. Another test of the LSP is presented in the Supplement, for data with constant sampling intervals where data points are missing randomly. This test is not so relevant here, since such data are not dealt with in this paper.

### 3.3 Wavelet power spectrum

The continuous wavelet transform is the convolution between a time series \( x(t) \) and the rescaled mother wavelet \( \Psi(t) \);

\[
W(t, \tau; x(t), \Psi(t)) = \int_{-\infty}^{\infty} x(t') \frac{1}{\sqrt{\tau}} \Psi^* \left( \frac{t' - t}{\tau} \right) dt',
\]

where the asterisk indicates complex conjugate. The wavelet power spectrum (WPS) is defined as \( |W(t, \tau)|^2 \), and the spectra are plotted vs. time and time-scale. The WPS is used here as a supplementary tool to the Fourier/Lomb–Scargle spectra. Time segments before and after the time interval where we have data were padded with zeros, as described in Torrence and Compo (1998). The region in \((t, \tau)\)-space affected by edge effects is the region above the white line in the upper part of the WPS-plot shown in, e.g., Fig. 5. Due to the uneven sampling of the data in this study, linear interpolation
has been performed prior to computing the WPS. At each time \( t \) there is a characteristic sampling period in the original time series, and hence a Nyquist period. This Nyquist period is marked as the lower white curve in the WPS plots. The WPS below that curve does not reflect observed variability.

We have chosen two wavelet functions as the basis for our study: the Morlet wavelet which is complex valued, and the Mexican hat wavelet (second derivative of a Gaussian) which is real valued. The wavelet power spectra from these two wavelet functions provide different information. The Mexican Hat wavelet function resolves the timing of spectral peaks precisely, while the scale resolution is poor. For the Morlet wavelet function the opposite is true.

4 Data

The scaling in seven proxy/multiproxy temperature reconstructions representing late Holocene temperature are analysed, in addition to six temperature reconstructions from the deep ice cores GRIP, GISP2 and NGRIP from Greenland, and EPICA, Taylor dome and Vostok from Antarctica. Information and analysis results from GISP2, NGRIP, Taylor and Vostok is provided in Supplement. From the available ice-core time series we extract sub-series covering only the Holocene and only the last glacial period, respectively. For the GRIP ice core we also extract a time series covering 0–85 kyr BP. Since the exact timing of the transition between the Holocene and the last glacial period is slightly different for Greenland and Antarctica, we have chosen the start and end of the time series carefully for each series, such that the transition is not contained in any of the “Holocene only” or the “glacial only” time series.

4.1 Proxy/multiproxy late Holocene temperature reconstructions

We have chosen seven proxy- or multiproxy based temperature reconstructions for our study, and in order to avoid the trend effect from anthropogenic warming we have
discarded data after 1850 AD (see Table 1). All time series are annually resolved. The Jones et al. (1998) multiproxy reconstruction represents Northern Hemisphere temperature. The Briffa et al. (2001) reconstruction represents the continental region 20–90° N and is constructed from tree rings. The Esper et al. (2002) reconstruction is also based on tree rings and represent the continental region 30–80° N. The Huang (2004) reconstruction is based on borehule temperatures, integrated with instrumental temperatures and the multiproxy reconstruction by Mann et al. (1999). The Moberg et al. (2005) multiproxy reconstruction represent Northern Hemisphere temperature, and is smoothed on the shortest time scales, so estimates of the scaling exponents are restricted to time scales from 4 years and longer. The Mann et al. (2009) multiproxy reconstruction represents global temperature, and is smoothed up to decadal time scales. The Neukom et al. (2014) multiproxy reconstruction represents Southern Hemisphere temperature.

4.2 The GRIP ice core

The European multinational research project “Greenland Ice Core Project” (GRIP) completed drilling a 3028 m deep ice core from central Greenland in 1992 (Dansgaard et al., 1993). Two GRIP data sets are used in this study, one with high temporal resolution covering 0–91 kyr BP (Ditlevsen et al., 1996), and one with lower temporal resolution covering 0–250 kyr BP (Greenland Ice-Core Project, GRIP; Johnsen et al., 1997). The high-resolution data set was provided by Peter Ditlevsen at the Centre for Ice and Climate, Niels Bohr Institute, University of Copenhagen, personal communication. Both data sets are used to estimate the scaling exponents, but the results shown in Sect. 5 are for the high resolution time series. The sampling times from the low-resolution data set were used when testing the LSP in Sect. 3. Both temperature reconstructions are based on $\delta^{18}O$. 
4.3 The EPICA ice core

The European Project for Ice Coring in Antarctica (EPICA) drilled two deep ice cores in Antarctica between 1996 and 2006. Here we focus on the core from dome C at the East Antarctic Plateau, covering the past 740,000 years (EPICA community members, 2004; Jouzel et al., 2007). The temperature reconstruction is based on $\delta D$.

5 Results

5.1 Results for late Holocene multiproxy reconstructions

Two approaches are used to detect a scale break from the spectra of the seven multiproxy temperature reconstructions. The first is to assume a scale break at exactly 100 years, and then estimate $\beta$ for long and short time scales, and determine the uncertainties for each estimate. By this approach we demonstrate that scale breaks may occur by chance from a mono-scaling model, without being statistically significant. The other approach is to use a procedure for automatic detection of a scale break from a two-scaling regimes hypothesis, and show that a wide range of time scales $\tau_c$ for the break, and a wide range of scaling exponents $\beta_1, \beta_2$, arise by applying the procedure to a Monte Carlo ensemble of monoscaling time series.

Figure 2 illustrates the procedure and results for the Moberg temperature reconstruction, using the first approach. The scaling exponent $\beta$ is estimated from the standard periodogram of the reconstructed data, for time scales shorter than $10^2$ yr ($\beta_{1,\text{data}}$) and for time scales longer than $10^2$ yr ($\beta_{2,\text{data}}$), as shown in Fig. 2b. A Monte Carlo (MC) ensemble of synthetic fGn’s with 2000 members is then constructed with $\beta_{1,\text{data}}$, and from the spectra (Fig. 2c), the same estimation technique is used to estimate $\beta_{1,\text{MC}}$ and $\beta_{2,\text{MC}}$ for each realization. From the distribution of the estimated $\beta_{1,\text{MC}}$ and $\beta_{2,\text{MC}}$, the 95% confidence ranges are computed. Figure 2d shows the mean and 95% confidence range for $\beta_{2,\text{MC}}$. Since the blue line ($\beta_{2,\text{data}}$) is within the confidence range for
a MC ensemble of fGn’s with $\beta = 0.8$, the mono-scaling hypothesis cannot be rejected. Results for all seven reconstructions are shown in Table 1.

For the Esper at al. (2002) reconstruction the estimate of $\beta_{1\text{, data}}$ is slightly outside the confidence range, but this is due a bias of the synthetic fBm for $\beta$ higher slightly higher than unity. This deviation should therefore be ignored.

From the second approach we obtain for each reconstruction two values of $\beta$ and a time for the scale break. The procedure is to fit two line segments with slopes $\beta_1$ and $\beta_2$ to the log-log spectrum, such that they join at $f = f_c = 1/\tau_c$. The two slopes and the transition frequency $f_c$ are the parameters to be fitted by an ordinary least-square procedure. Results for the seven temperature reconstructions are provided in Table 2, where also the differences in $\beta$ values are included. The scale-break hypothesis of Lovejoy and Schertzer (2012) states that the the difference $\beta_2 - \beta_1$ should be around unity. This procedure has also been tested on a Monte Carlo ensemble of mono-scaling fGn’s. Figure 3 shows a histogram of the differences in estimated $\beta_2$ and $\beta_1$. The histogram shows that the scale breaks detected by this procedure in the multiproxy records are not unlikely to be detected in mono-scaling records, i.e., their detection does not reject the mono-scaling hypothesis. A histogram of $\tau_c$ also shows a broad distribution, (figure not shown).

### 5.2 Results for ice core time series

For the time series plots, time on the horizontal axis is given in years BP (before present), where “present” is defined as 1950 AD. The LSP analysis is presented in a double-logarithmic plot. The raw LSP is plotted in gray, while the log-binned LSP is marked by black points. The spectral index $\beta$ is estimated from the log-binned LSP in the region shown by the blue line. Finally, the blue, shaded area indicate the 95% confidence range estimated from an ensemble of synthetic fGn’s with $\beta$ and variance estimated from the log-binned LSP. The plot of the wavelet power spectra (WPS) is included in this section only for the GRIP Holocene records, remaining WPS are presented in Supplement.
For the last glacial period, we present time series and LSP for two time intervals of unequal length, one \( \approx 25 \) kyr, and one covering a longer part of the glacial period (\( \approx 80 \) kyr). The shorter record has better sampling resolution, but provides information about scaling only up to a few kyr. The longer record allows exploration of the scaling behavior up to more than ten kyr. Results are also included for a combined Holocene/last glacial period time series from the GRIP ice core to illustrate that analysis of such records will be dominated by the glacial climate and suppress the characteristics of Holocene climate.

5.2.1 Results from the GRIP ice core

Figure 4a shows the \( \delta^{18}O \) time series of the Holocene part of the high-resolution GRIP ice core, and Fig. 4b the LSP from the same time series. Figure 4c displays the same time series as shown in (a), but with the earliest 2500 yr removed. Figure 4d shows the LSP for the time series in (c). The rationale for removing the earliest part of the Holocene record can be seen from Fig. 4a, where one observes a decrease in \( \delta^{18}O \) around 8 kyr BP. This particular decrease is often observed in paleotemperature records from the Northern Hemisphere, and especially in records from the North-Atlantic region. The feature is known as the 8.2 kyr event, and the temperature change was probably caused by a large pulse of freshwater into the North-Atlantic Ocean associated with the collapse of the Laurentide ice sheet (Alley and Agustsdottir, 2005). In Fig. 4b, \( \beta \) is estimated to be \( \approx 0.3 \) for time scales up to \( 10^3 \) yr. No scale break is detected on centennial time scales. The low value of \( \beta \) is typical for local temperature data from continental sites (Blender and Fraedrich, 2003; Fraedrich and Blender, 2003). On time scales longer than a millennium we can infer a higher \( \beta \), but still \( \beta < 1 \). Since the 8.2 kyr event might affect the scaling we also analysed the shorter record (Fig. 4c). The LSP for this time series is essentially flat. Figure 5 shows the Mexican hat and Morlet wavelet power spectra for the full Holocene section of the GRIP ice core. The 8.2 kyr event clearly increases the power at millennial time scales, and this event is the source of the increased power observed at that time scale in Fig. 4b. From the LSP of the
Holocene part of the low-resolution GRIP time series we estimate $\beta \approx 0.1$ (not shown in figure).

Figure 6a displays a short $\delta^{18}O$ time series for the GRIP ice core from the last glacial period, and Fig. 6b the LSP for the same time period. Figure 6c shows a longer time series from the last glacial period, and Fig. 6d the power spectrum for this long time period. In Fig. 6a, c the Dansgaard–Oeschger (DO) events are observable as rapid warming over decadal time scales, followed by more gradual cooling (Bond and Lotti, 1995). In Fig. 6b we find $\beta \approx 1.7$ for time scales longer than $10^2$ yr and shorter than $10^4$ yr. For the longer time series in Fig. 6c, we estimate $\beta \approx 1.4$ in Fig. 6d on the same time scales as in Fig. 6b. On centennial time scales and shorter, the spectrum is flatter, most likely due to the DO-events. This means that a hypothesis of a scale break at centennial time scales is plausible under glacial climate conditions, even though such a scale break could not be identified from the Holocene time series. From the low-resolution GRIP data set we estimate $\beta \approx 1.3$ for time scales longer than centennial, and a scale break is seen at this scale (figure not shown).

Figure 7a shows the past 85 kyr time series of the high-resolution GRIP ice core, and Fig. 7b the LSP for the same time series. In Fig. 7b, $\beta \approx 1.4$ for time scales longer than centennial, and a scale break is visible at this scale. The LSP in Fig. 7 is very similar to that in Fig. 6, indicating that the information from the Holocene is suppressed in the LSP of this time series.

### 5.3 Results from the EPICA ice core

Figure 8a shows the Holocene time series of the EPICA ice core, and Fig. 8b the LSP for the same time series. In Fig. 8a the Antarctic equivalent to the Northern Hemisphere Holocene climate optimum (HCO) occurred between 11 500 and 9000 yr BP (Masson et al., 2000). In Fig. 8b, $\beta \approx 0.3$ for time scales shorter than $10^3$ yr.

Figure 9a shows a short time series of the EPICA ice core from the last glacial period, and Fig. 9b the power spectrum for the same time period. Figure 9c shows a longer time series from the last glacial period, and Fig. 9d displays its power spectrum. We
observe from the time series in Fig. 9a that the fluctuations do not coincide with the DO events in the GRIP ice core with respect to timing and amplitude. Like the glacial part of the GRIP ice core the EPICA glacial time series Fig. 9a, c have higher fluctuation levels than the Holocene counterpart. In Fig. 9b we estimate $\beta \approx 1.5$ for $10^3 \text{ yr} < \tau < 10^4 \text{ yr}$. For the longer time series, the LSP is estimated in Fig. 9d, and we find $\beta \approx 1.8$ between $10^3 \text{ yr}$ and up to more than $10^4 \text{ yr}$. The scale break in these figures appears at $10^3 \text{ yr}$, and no scale break is observed at centennial time scales.

6 Discussion and conclusions

In this paper we have examined a number of paleoclimatic temperature records to assess the feasibility of detection with confidence multiple scaling regimes in Holocene climate, and in particular a break in scaling around centennial time scales. Seven proxy/multiproxy reconstructions from the late Holocene have been selected for analysis due to high temporal resolution and coverage in time, and six reconstructions from deep ice cores sampled at Greenland and Antarctica also meet our requirements for temporal coverage and resolution.

For the seven proxy-based temperature reconstructions, our first approach was to assume a break at exactly 100 years. Obviously there are few data points available for estimation on the longer scales using this procedure and the estimated values of $\beta_2$ are within the uncertainties of a mono-scaling model for all seven reconstructions. The scale break is therefore not statistically significant. For the second approach, our systematic procedure detects a break in scaling for all reconstructions. The time scale for the break varies significantly between reconstructions and is in most cases not even located near centennial time scales. The differences $\beta_2 - \beta_1$ varies over a great range and takes on both positive and negative values. This procedure has also been tested on a Monte Carlo ensemble of fGn’s and demonstrates that we will find such apparent breaks even in data that should not have breaks.
In ice-core data, a scale break at centennial time scales can only be seen in records from the last glacial period. The time series for the Holocene from the GRIP and EPICA ice cores both exhibit weak persistent scaling (Figs. 4 and 8). The scaling exponent is estimated to $\beta \approx 0.3$ for both ice cores up to millenium time scale. No break in scaling can be observed at centennial time scale. The low value of $\beta$ obtained is consistent with the scaling exponents observed over land from the paleoclimate model run presented in Blender et al. (2006). On time scales longer than millenial we do not have enough data points to make confident estimates of $\beta$. From the wavelet power spectra we argue that the increase in power seen at the longest time scales in the GRIP and EPICA LSP’s can be attributed to the 8.2 kyr event, and (for EPICA) similar but weaker time-localised events.

The scaling properties of the GRIP and EPICA last glacial period are significantly different from the Holocene. A scale break at centennial time scales is identified with confidence from Figs. 6 and 9. We interpret this scale break as being associated with the variability of Dansgaard–Oeschger events and teleconnections to the Southern Hemisphere. A number of theories and models exist for the mechanism of these events, see e.g., Dokken et al. (2013). This and other studies indicate that this variability is internal and not a direct response to external forcing.

From the GRIP time series including both the Holocene period and the last glacial period we obtain an LSP very similar to that of the glacial climate (Fig. 7). Since the glacial climate state is the dominating state in the Pleistocene, the Holocene temperature variability is strongly suppressed when time series covering 100 kyr or longer are used to estimate scaling exponents. Our analysis of Holocene records, on the other hand, shows that a scale break on centennial time scales is not a universal feature, and in those cases it appears to be present, it cannot be detected with sufficient certainty.

Faced with the results we have presented here one may ask what the practical implications are. Is scaling in climatic time series a useful concept? Our perception is that a scaling law may be useful as a statistical (stochastic) model when a causal de-
scription turns out to be very complex, i.e., when the viable alternative is something like a general circulation model. Such a statistical model does not have to exhibit long-memory scaling (a more standard model is a short-memory autoregressive process), but there is strong evidence, for internal variability of surface temperature data, that an fGn is a much better model than an AR(1) process for time scales at least up to centuries (Rypdal and Rypdal., 2014). Thus, for prediction on time scales up to decades, a mono-scaling model with $\beta < 1$ is what should be used, (Lovejoy et al., 2015). More interesting, however, is whether long-memory scaling has implication for prediction on century time scales and beyond, and here the issue of non-stationary scaling ($\beta > 1$) for such time scales becomes crucial. What is the proper value of $\beta$ to use in such prediction efforts in a warming Holocene climate? The conclusion we draw from our results is that, unless we ignore the knowledge that the present climate state of the Earth is an interglacial, we should still use $\beta < 1$. One argument that can be raised against that conclusion is that, even though we cannot reject the monoscaling hypothesis based on available Holocene data, we cannot exclude that two scaling regimes is true either. Moreover, the latter is supported from records spanning hundreds of kyr which encompass both glacial and interglacial climate. This stalemate reflects that we are faced with a model selection problem where the outcome depends on which available knowledge we prefer to emphasise.

The multiscaling model stresses the information we have on scaling in the second-order statistics such as power spectra ($\beta > 1$) on time scales up to hundreds of kyr (Pleistocene scaling), and infers that this scaling should be a guideline for prediction independent of whether the initial state is glacial or interglacial. It essentially ignores the fact that Pleistocene climate is characterized by several intermittencies, (Lovejoy and Schertzer, 2013). The dominating Pleistocene climate state is the glacial, and temperature proxies from the last glacials take the form of a non-gaussian intermittent stochastic process, displayed in its full glory by the Dansgaard–Oeschger events. Intermittency implies that the pdfs are leptokurtic on short time scales and typically approaching gaussian on longer time scales. Hence structure functions of higher order
than two are needed to characterize the process. For a gaussian process the power spectral density can be inferred from the second-order structure function and hence does not convey information beyond second-order statistics. Moreover, Pleistocene climate is characterized by the glacial–interglacial transitions, which adds more intermittency, and all this intermittency makes prediction based only on Pleistocene scaling very difficult.

The monoscaling model, on the other hand, ignores the information available on time scales beyond the Holocene, but makes use of the fact that our present climate state is an interglacial, and that second-order statistics is sufficient to describe the scaling on the time-scales that is available to us in the Holocene. As discussed above, monoscaling can be rejected by data that goes way beyond the Holocene, but there is no statistically significant, empirical evidence that the scaling inferred by glacial-state data is present in the interglacial climate state. Huybers and Curry (2006) suggest that it is, and speculate that it is a nonlinear response to Milankovich forcing, but a solid physical theory that describes this hypothetical mechanism is not yet on the horizon.

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Table 1. Results for 7 late Holocene temperature reconstructions, assuming a scale break at exactly 100 years.

<table>
<thead>
<tr>
<th>Reconstruction</th>
<th>Time period</th>
<th>$\beta_{1,\text{data}}$</th>
<th>conf. range for $\beta_{1,MC}$</th>
<th>$\beta_{2,\text{data}}$</th>
<th>conf. range for $\beta_{2,MC}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jones et al. (1998)</td>
<td>1000–1850</td>
<td>0.5</td>
<td>(0.4, 0.7)</td>
<td>1.2</td>
<td>(−0.8, 1.7)</td>
</tr>
<tr>
<td>Briffa et al. (2001)</td>
<td>1402–1850</td>
<td>0.6</td>
<td>(0.4, 0.8)</td>
<td>2.9</td>
<td>(−2.0, 3.0)</td>
</tr>
<tr>
<td>Esper et al. (2002)</td>
<td>831–1850</td>
<td>1.3</td>
<td>(0.8, 1.2)</td>
<td>1.2</td>
<td>(0.2, 3.3)</td>
</tr>
<tr>
<td>Huang (2004)</td>
<td>1500–1850</td>
<td>0.7</td>
<td>(0.6, 1.0)</td>
<td>2.3</td>
<td>(−4.4, 6.0)</td>
</tr>
<tr>
<td>Moberg et al. (2005)</td>
<td>0–1850</td>
<td>0.8</td>
<td>(0.6, 1.0)</td>
<td>1.2</td>
<td>(0.0, 1.5)</td>
</tr>
<tr>
<td>Mann et al. (2008)</td>
<td>500–1850</td>
<td>2.5</td>
<td>(1.9, 2.6)</td>
<td>1.6</td>
<td>(1.5, 3.1)</td>
</tr>
<tr>
<td>Neukom et al. (2014)</td>
<td>1000–1850</td>
<td>0.6</td>
<td>(0.4, 0.8)</td>
<td>1.3</td>
<td>(−0.8, 1.9)</td>
</tr>
</tbody>
</table>
Table 2. Results for 7 late Holocene temperature reconstructions, using procedure for automatic detection of scale break.

<table>
<thead>
<tr>
<th>Data set</th>
<th>$\beta_{1,\text{data}}$</th>
<th>$\beta_{2,\text{data}}$</th>
<th>$\tau_c$ (yr)</th>
<th>$\beta_{2} - \beta_{1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jones et al. (1998)</td>
<td>0.5</td>
<td>0.9</td>
<td>38</td>
<td>0.4</td>
</tr>
<tr>
<td>Briffa et al. (2001)</td>
<td>0.9</td>
<td>0.2</td>
<td>22</td>
<td>−0.7</td>
</tr>
<tr>
<td>Esper et al. (2002)</td>
<td>1.4</td>
<td>1.0</td>
<td>38</td>
<td>−0.4</td>
</tr>
<tr>
<td>Huang (2004)</td>
<td>0.8</td>
<td>2.2</td>
<td>94</td>
<td>1.4</td>
</tr>
<tr>
<td>Moberg et al. (2005)</td>
<td>0.7</td>
<td>2.6</td>
<td>353</td>
<td>1.9</td>
</tr>
<tr>
<td>Mann et al. (2008)</td>
<td>3.1</td>
<td>0.9</td>
<td>47</td>
<td>−2.2</td>
</tr>
<tr>
<td>Neukom et al. (2014)</td>
<td>0.5</td>
<td>0.8</td>
<td>9</td>
<td>0.3</td>
</tr>
</tbody>
</table>
Figure 1. Value of estimated $\beta$ vs. true $\beta$ from 100 realizations of synthetic data. (a) Temporal sampling equal to the low-resolution GRIP Holocene time series. (b) Temporal sampling equal to the low-resolution GRIP last glacial time series.
Figure 2. (a) The Moberg et al. (2005) reconstructed temperature for the Northern Hemisphere. (b) Estimated values of $\beta_1$ and $\beta_2$. (c) 95% confidence range for periodograms in Monte Carlo study. (d) 95% confidence range for estimates of $\beta_2$. 
Figure 3. Differences in $\beta_2$ and $\beta_1$ for a Monte Carlo ensemble with 2000 members of synthetic LRM processes with $\beta = 0.7$. The black arrows indicate the differences from the multiproxy reconstructions.
Figure 4. (a) $\delta^{18}O$ anomalies from the Holocene part of the high-resolution GRIP ice core. (b) Lomb–Scargle periodogram. The raw LSP is shown in gray, the log-binned version by black dots. $\beta$ is estimated from the log-binned LSP in the region marked by the blue line. The confidence range is shown by the blue, shaded area, estimated from a Monte Carlo ensemble of synthetic fGns with the estimated value of $\beta$ and variance from the log-binned LSP. (c) Same figure as in (a) except the oldest section has been removed. (d) Lomb–Scargle periodogram for the time series in (c).
Figure 5. Top: the Mexican hat wavelet power spectrum for the Holocene part of the GRIP ice core, and bottom: the Morlet wavelet power spectrum for the same time series. The lower white curve in each plot denotes the varying Nyquist frequency, and the upper white curve the area affected by edge effects. Studies are restricted to the area between the two curves. The color bar to the right of the figure is used to indicate the magnitude of the wavelet power.
Figure 6. (a) $\delta^{18}$O anomaly time series from the last glacial period of the high-resolution GRIP ice core. (b) Lomb–Scargle periodogram for the time series in (a). (c) Longer $\delta^{18}$O anomaly time series from the last glacial period of the GRIP ice core. (d) Lomb–Scargle periodogram for the time series in (c).
Figure 7. (a) $\delta^{18}O$ anomalies from the past 85 kyr of the high-resolution GRIP ice core. (b) LSP for the same time series.
Figure 8. (a) $\delta D$ anomalies from the Holocene part of the EPICA ice core. (b) Lomb–Scargle periodogram.
Figure 9. (a) δD anomalies from the last glacial period part of the EPICA ice core. (b) Lomb–Scargle periodogram for the time series in (a). (c) Longer δD anomaly time series from the last glacial period of the EPICA ice core. (d) Lomb–Scargle periodogram for the time series in (c).