



Identifying natural contributions to late Holocene climate change

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ARTICLE INFO

Article history:

Received 16 June 2011

Accepted 9 September 2011

Available online 18 September 2011

Keywords:

climate change

natural climatic variations

wavelet

Svalbard

Greenland

ABSTRACT

Analytic climate models have provided the means to predict potential impacts on future climate by anthropogenic changes in atmospheric composition. However, future climate development will not only be influenced by anthropogenic changes, but also by natural variations. The knowledge on such natural variations and their detailed character, however, still remains incomplete. Here we present a new technique to identify the character of natural climate variations, and from this, to produce testable forecast of future climate. By means of Fourier and wavelet analyses climate series are decomposed into time–frequency space, to extract information on periodic signals embedded in the data series and their amplitude and variation over time. We chose to exemplify the potential of this technique by analysing two climate series, the Svalbard (78°N) surface air temperature series 1912–2010, and the last 4000 years of the reconstructed GISP2 surface temperature series from central Greenland. By this we are able to identify several cyclic climate variations which appear persistent on the time scales investigated. Finally, we demonstrate how such persistent natural variations can be used for hindcasting and forecasting climate. Our main focus is on identifying the character (timing, period, amplitude) of such recurrent natural climate variations, but we also comment on the likely physical explanations for some of the identified cyclic climate variations. The causes of millennial climate changes remain poorly understood, and this issue remains important for understanding causes for natural climate variability over decadal- and decennial time scales. We argue that Fourier and wavelet approaches like ours may contribute towards improved understanding of the role of such recurrent natural climate variations in the future climate development.

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1. Introduction

Here we present an empirical technique to identify natural climatic variations in climate records, and from this, to hindcast and forecast climate variations. Most meteorological series display significant decadal or multi-year periodic behaviour, which so far have not been fully included in analytic climate models (e.g., Solomon et al., 2010), mainly because of incomplete knowledge on the detailed character of such variations. For example, the Pacific Oscillation that gives rise to El Niño and La Niña has been known for over a century, and in the North Atlantic a similar oscillation, the North Atlantic Oscillation (NAO), is known to influence the weather in this region. During the last years there has therefore been an increasing realisation of important oscillatory phenomena in the Earth's global weather system, as knowledge on such cyclic variations is important to discriminate

between natural and anthropogenic influences on contemporary climate change.

This suggests that a study of cyclic natural variations is timely for improving understanding of both present and future climate variations. Most climate models are trying to solve the complex problem of climate forecasting from first principles: The Navier–Stokes equations, the thermodynamics of phase changes of atmospheric water, the detailed radiation budget of the Earth and atmosphere and ocean dynamics. Our approach is different from this, representing an empirical bottom-up approach to climate modelling. We begin our analysis on a site-specific scale, using existing climate series.

Below we demonstrate the potential importance of such a bottom-up approach by analysing two Arctic temperature series, representing different time scales: (1) the Svalbard 1912–2010 surface air temperature record, and (2) the central Greenland GISP2 reconstructed surface temperature series (Alley, 2000). The Svalbard (78°N) data series is unique by being the longest meteorological record from the High Arctic, a region usually considered very sensitive to global climate changes. The second series, the GISP2 data has merit because of the long time range represented (back to the Eemian interglacial), and because the Greenland air temperature appears to vary in overall

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concert with the temperature of much of the planet (Chylek and Lohmann, 2005; Brox et al., 2009). Here we chose to focus on the most recent 4000 years of the GISP2 series, as the main thrust of our investigation is on climatic variations in the recent past and their potential for forecasting the near future. In addition, this part of the GISP2 series shows an overall linear temperature trend, which simplifies the following analysis. By choosing these two data series, we want to draw attention to the usefulness of not only long proxy series, but also standard meteorological series, which are much shorter than most proxy records. Both types of data series apparently are useful for a natural cycle based climate analysis, although on different time scales. As one example, it might be difficult from a short meteorological series to characterise fully the character of a 60–65 yr oscillation, such as, e.g., the AMO. Likewise, from a long proxy data series with 20–50 yr resolution it would be impossible to resolve the character of decadal scale oscillations. However, here our main focus is the identification of natural cyclic variations, and only secondary the attribution of physical reasons for these.

2. Wavelet analyses

Visual inspection of climate data series often suggests the existence of one or several recurrent variations. However, describing the character (persistence, period and amplitude) of such cyclic patterns is difficult, as the variations quite often come and go, lasting only for a limited period at each appearance. For this reason, they may prove difficult to characterise fully from a normal Fourier power spectrum. Especially the dynamics over time of the individual cycles can be difficult to analyse. However, as will be shown below, Fourier analysis remains an extremely valuable tool for the identification of such recurrent natural climate variations.

To overcome the problem encountered when cyclic variations change their period and amplitude, we here also employ wavelet analysis to identify and describe oscillating variations in climate series as a supplement to the Fourier analysis. Wavelet analyses are able to pick up even oscillations that last for a relatively short time and change their phase between one appearance and the next. Thus, wavelets transform represents an analysis tool well suited to the study of nonstationary processes occurring over finite spatial and temporal domains. Among other things, this technique it is well suited to visualise the frequency content of a signal as it varies through time. Since its introduction by Jean Morlet in 1983, wavelet analysis has gradually found application in several fields of sciences, such as, e.g., seismic signal detection, turbulence, fractal research, etc. By this, wavelet analysis is becoming a common tool for analysing localised variations of power within time series.

The Continuous Wavelet Transform (CWT) is used to decompose a signal into wavelets, small oscillations that are highly localised in time. Whereas a normal Fourier transform decomposes a signal into infinite length sines and cosines, effectively losing all time-localization information, the CWT's basis functions are scaled and shifted versions of the time-localised mother wavelet. Thus, the CWT is used to construct a time–frequency representation of a signal that offers very good time and frequency localization.

Many data series contain cyclic variations that are nonstationary, varying in both amplitude and frequency over long periods of time, which makes identification of such variations difficult. However, by decomposing time series into time/frequency space by wavelet analysis, it becomes possible to extract information on both the amplitude and variation over time of any periodic signal within the series, but only for that part of the signal which can be decomposed into sinusoidal components. An overall trend affecting the whole time series considered will therefore not be found by this technique. The resulting wavelet diagram provides information on periodic behaviour in the data series, making it possible to determine both the dominant modes of variability and how these modes vary with time. This, in turn, provides an important tool for understanding

the nature of the main drivers behind observed cyclic variations of different phenomena.

Three wavelet types may be considered for analysis of time series; the Paul-, the GaussDeriv- and the Morlet wavelets. All three wavelets offer very good time localization, but the Paul wavelet localises most efficiently in the time domain. The GaussDeriv wavelet is slightly less efficient in this respect, and the Morlet is the least efficient of the three, although it still offers very good localization in the time domain. The greater differences between the three types of wavelets tend to be in the frequency domain. For a given count of evident oscillations in the wavelet, the Morlet offers the best frequency localization, the GaussDeriv wavelet is slightly less efficient, and the Paul wavelet is the least efficient in this respect (SeaSolve, 2003). To ensure efficient use of the Morlet wavelet's superior frequency localization, the number of frequencies (n) in the wavelet spectrum must be chosen high enough to ensure detection of closely spaced frequency components, even though this usually results in substantially increased computing time and memory requirements.

Here we chose to make use of the Morlet wavelet, because superior frequency localization is essential to determine the most likely physical origin of the oscillations identified. At the same time, the Morlet wavelet still provides a very good localization of the oscillations in the time domain. Specifying high Morlet wave numbers (Adj) can offer significantly improved frequency resolution when used with large data sets. However, to prevent washing out spectral information, it is also necessary to be cautious of using too high wave numbers with data that have too few oscillations or too short a sampling length. The wavelet should not be over specified and the data sequence being analysed should usually have more oscillations than the wavelet used. In our analysis we therefore limited the Morlet wave number to 10.

In our analysis we calculated the complex wavelet, which is the normal choice for this kind of analysis (SeaSolve, 2003). Another option is to calculate the real component of the complex wavelet in the time domain. The nature of an oscillation with the CWT spectrum will vary greatly with whether the wavelet is real or complex (SeaSolve, 2003), which can be disconcerting if the difference is not realised. The frequency domain transform of a real wavelet is symmetric about frequency 0 and contains two peaks, and produces power only at those times where the oscillation is at an extreme or where a sharp discontinuity occurs. The complex wavelet, in contrast, will evidence a constant power across the time duration of the oscillation, combining both positive and negative peaks into a single broad peak, thereby more clearly showing the extent of the oscillation in both the time and frequency domain.

To avoid wraparound effects that arise as a consequence of non-periodicity in both the data and the response function (daughter wavelet), zero padding is needed equal to the half the length of the non-zero elements in the daughter wavelet's frequency response. Usually zero padding to twice the data length insures that no wrap-around effects are possible anywhere in the spectrum. By sufficient zero padding wraparound effects are eliminated but a different issue then arises, as it is likely that a discontinuity is introduced at the end of the data series. Further, power is reduced near the edges of the spectrum with the introduction of the zeros into the convolution. This zone of edge effects is known as *the cone of influence*, inside which spectral information is not likely to be as accurate regardless of whether or not zero padding is used. If zero padding is not used, wraparound effects can occur at low frequencies. If zero padding is used, the spectral powers may be diminished within the cone of influence (SeaSolve, 2003). The consequence of this is that if a ridge of spectral power shows up inside the cone of influence it is likely to be real, but perhaps shown with diminished power. Likewise, if a ridge of spectral power outside the zone of edge effects continues into the cone of influence, it is likely to represent a persistent spectral signature. Here we used zero padding and computed the cone of influence using e-folding distances as described by Torrence and Compo (1997).

In general, according to the Nyquist–Shannon sampling theorem (Shannon, 1998), only frequencies lower than $f_s/2$ should be considered in the analysis, where f_s is representing the sampling frequency. As an example, for a data series representing annual values only frequencies lower than 0.5 year^{-1} should be considered, corresponding to periods longer than 2 years.

Wavelet analysis has previously been brought into use in climate studies (e.g. Lau and Weng, 1995; Torrence and Compo, 1997; Baliunas et al., 1997; Isaksson et al., 2005; Butler et al., 2007), but until now the technique only has received limited interest from the climate community in general. The modest interest may partly be explained by the intense focus on analytic climate modelling, and partly by the fact that most papers on wavelet analysis tend to employ a difficult mathematical language. The full potential of wavelet analysis in climate studies therefore presumably still has to unfold. The paper by Torrence and Compo (1997), however, did much to make wavelet analyses be wider known, and the subsequent appearance of commercial software packages enabling wavelet analysis without prior personal programming have now for the first time made the application of wavelet analysis relatively easy. In the present study, the Wavelets package AutoSignal v.1.7 by SeaSolve Software Inc. was used for analysis. The core computations in this software generally follow the algorithms specified by Torrence and Compo (1997).

Summing up, wavelet analysis assists in identifying and describing patterns in data series, much in the same way as a geologist identifies and describes textures and structures in a sedimentary profile to provide a detailed knowledge base for the interpretation of the origin of the deposit. By this wavelet analysis is much more than just another statistical approach to data analysis.

3. The Svalbard temperature record

The wavelet-based analysis approach is suitable for being applied to standard meteorological observational records, even though most of these are relatively short (<150 years). As an example of this, we here analyse the Svalbard (78°N) meteorological data series 1912–2010 (Fig. 1), which is the longest meteorological record from the High Arctic.

Special climatic interest has often been attached to the Svalbard region because of the high latitude and the fact that this part of the Arctic apparently displays an extraordinary high climatic variability, partly reflecting global temperature trends. This was recognised early by both Ahlmann (1953) and Lamb (1977), and later by Rogers et al. (2005), but also in the third IPCC report (Houghton et al., 2001)

attention was specifically drawn to the very high climatic sensitivity of Svalbard.

Climatic variations in the Svalbard region during the 20th century are documented by monthly meteorological data since November 1911 (Førland et al., 1997). A prominent feature of the record is a marked warming around 1920, which within 5 years changed the mean annual air temperature (MAAT) at sea level from about -9°C to -4°C . This remains one of the most rapid surface air temperature increases documented anywhere during the instrumental period. It is, however, not known if the low starting temperature in the record is typical for Little Ice Age conditions in Svalbard, or if represents just the culmination of an especially cold period.

The meteorological station is located at the Svalbard Airport (24 m asl.), about 3 km NW of the main settlement Longyearbyen ($78^\circ13'\text{N}$, $15^\circ33'\text{E}$), central Spitsbergen, near the shore of the big fjord Isfjorden. Monthly temperature data were obtained from the eKlima portal run by the Norwegian Meteorological Institute, and MAAT values 1921–2010 calculated from this.

The Svalbard meteorological record is a composite record, consisting of observations made at 4 different meteorological stations, located at different places along the shore of the fjord Isfjord (Førland et al., 1997). However, the absences of visible irregularities in the wavelet diagram (Fig. 3), corresponding to known station changes, testify to the quality of the homogenisation procedure carried out by Førland et al. (1997).

The Svalbard temperature record (Fig. 1) is characterised by rapid warming 1917–1922, terminating the Little Ice Age in Svalbard, a warm period lasting until around 1955, a relatively cold period lasting to about 1990, and a renewed warming lasting at least until 2006. A number of decadal-scale variations are apparently superimposed on this generalised pattern of change. The overall variations displayed by the mean annual air temperature are mainly derived from winter temperature variations, while the summer temperature only shows relatively small variations. Since about 1990 the Svalbard MAAT has increased about $3\text{--}4^\circ\text{C}$, but it is not possible to determine if this temperature increase is the leading edge of a more permanent increase as suggested by most climate models, or merely represents a typical decadal scale oscillation. Indeed, decreasing MAAT since 2006 suggests an oscillation.

Before 1912 only scattered temperature records are known from Svalbard, but it is entirely possible that the very cold initial period 1912–1917 represents a temperature minimum following a previous period with somewhat higher temperatures. If so, the linear trend of 0.23°C per decade calculated for the entire MAAT record 1912–2010 is likely to indicate an unrealistic high overall temperature increase rate.

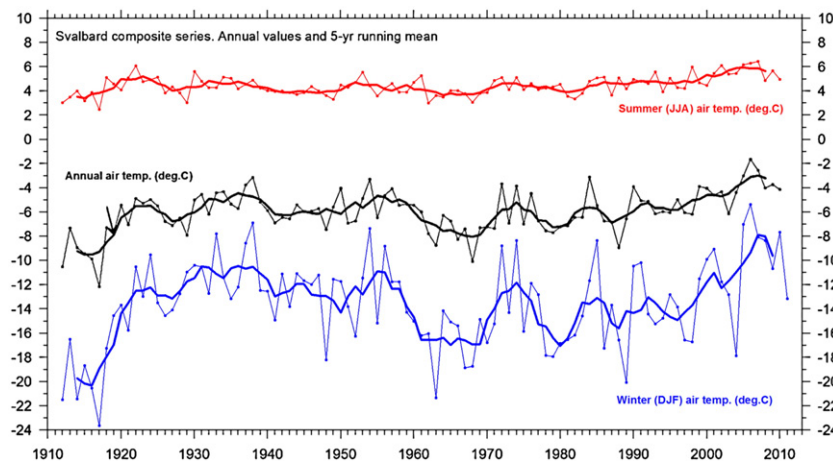


Fig. 1. The Svalbard temperature record 1912–2010, showing the mean annual air temperature (MAAT; black), the average summer temperature (JJA; red), and the average winter temperature (DJF; blue). Thin lines show annual values, and thick lines show the simple 5 year average. The linear MAAT increase 1912–2010 is 0.23°C per decade. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.1. Fourier analysis of the Svalbard record

A Fourier series is an expansion of a periodic function in terms of an infinite sum of sines and cosines. The computation and study of Fourier series (harmonic analysis) is extremely useful as a way to break up an arbitrary periodic function into a set of simple terms that can be solved individually, and then recombined to obtain the solution to the original problem or an approximation to it.

Before carrying out the Fourier analysis on the Svalbard MAAT series, the data series was taken at face value and the 1912–2010 linear trend of $0.23\text{ }^{\circ}\text{C}$ was removed. The result of the Fourier analysis is shown in Fig. 2, from which the Svalbard MAAT record is seen to be dominated by three periods of about 68.4, 25.7 and 16.8 years long, all with amplitude greater than $0.8\text{ }^{\circ}\text{C}$. These three periods all exceeds the 90% critical limit (null hypothesis is white noise), meaning that only 1 of 10 separate random noise signals would the largest peak present achieve this height strictly due to random chance. The 68.4 yr peak even exceeds the 99.9% critical limit, indicating that there is less than a 1 in 1000 probability this peak arose from chance. In addition to these dominant periods, four periods with amplitude about or greater than $0.5\text{ }^{\circ}\text{C}$ also are of importance. These periods have lengths of about 36.7, 12.3, 8.7 and 5.1 years, respectively.

Strong periods like the 68.4 and 25.7 and 16.8 year periods may have weaker harmonics if they are not perfect sine variations, which might explain some of the shorter periods observed by the Fourier analysis, e.g. 36.7, 12.3 and 8.7 years, respectively. Such shorter periods are therefore not providing new information as to their origin, except that the fundamental variation deviates from being a perfect sine variation.

The 10.5 year period with about $0.4\text{ }^{\circ}\text{C}$ amplitude may possibly represent a solar signal in the record, while the stronger 8.7 year period is nearly identical to a well known lunar orbital period (8.85 years), and may therefore not represent a harmonic of the longer 16.8 year period. The possible origin of some of the other identified periods will be commented further below.

3.2. Wavelet analysis of the Svalbard record

Before analysing the Svalbard temperature record it was detrended by fitting a linear trend to the data and then subtracting this from the data. The detrended data set was then decomposed by a continuous wavelet transform, whereby a time–frequency representation of the embedded signals was constructed with good time and frequency resolution (Fig. 3). As the Fourier analysis (Fig. 2) suggested the existence of

more than 10 oscillations in the data set, we specified a wave number of 10 (the Morlet wavelet takes wave numbers from 6 to 500).

The resulting visual representation of the spectral composition of the Svalbard MAAT record should be regarded much like a topographic map with contour lines for altitudes. Any part of the diagram is potentially displaying important information, as are systematic contour patterns (ridges and valleys) in a topographic map, and should not be ignored in the analysis. Within the cone of influence, however, spectral powers may be diminished compared to their real values. By this approach we differ from e.g. Isaksson et al. (2005), which calculated the standard deviation for the wavelet values, and in their interpretation only considered values deviating more than two standard deviations from the mean value. In principle, a cautious approach like this could also be applied for the study of a normal topographic map, but this would clearly exclude much potentially valuable topographic information from the following analysis of terrain surface forms. For that reason, even though we in the following analysis pay direct attention to the highest values found by the wavelet analysis, we also consider the remaining amount of information, such as expressed by the general ‘topography’ of the spectral diagram.

Wavelet analysis revealed several cyclic variations in the Svalbard meteorological record. Since 1912 three dominant periods of about 83, 62, 26 and 16.8–16.7 years characterise the entire record. A weaker oscillation of about 36–37 years is also visible. All these periods have been stable with regard to both magnitude and frequency, even when extending outside the cone of influence, where spectral powers may be artificially diminished because of the zero padding. In addition to this, a number of shorter periods were also identified: about 12.5–11.6 and 8.8–7.8 years. In contrast to the longer periods not all of these shorter periods have been stable phenomena. The 12.5 year period was initially strong, but the signal declined somewhat in magnitude and period (now 11.6 years) over the observational period. Concurrent with this, the about 8.8 year period increased in importance until around 1985, after which a weakening apparently has begun, although perhaps a zero padding effect. Along with this a slight frequency increase has taken place, so the modern period length is somewhat shorter, about 7.8 years. The shorter periods all are relatively weak, and the main control on the Svalbard MAAT record has clearly been exercised by the longer periodic variations; especially the 83, 62, 26 and 16.8–16.7 year cycles.

Several of the periods identified by the wavelet analysis (Fig. 3) are recognised also by the Fourier analysis (Fig. 2) Some of the periods identified may be interrelated: The 62, 37–36, 26 and 16.8–16.7 year

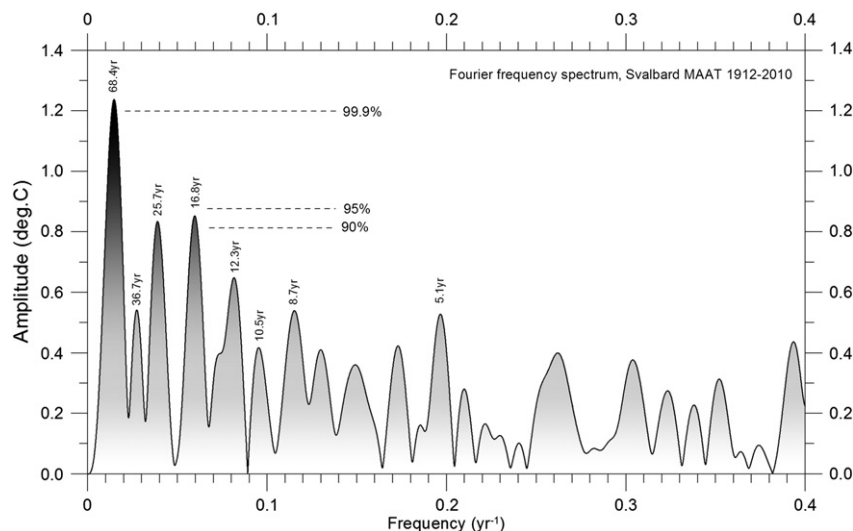


Fig. 2. Fourier analysis (using Best Exact N composite algorithm) of the detrended Svalbard 1912–2010 MAAT series. The record is dominated by three periods of about 68.4, 25.7 and 16.8 years long, all with amplitude greater than $0.8\text{ }^{\circ}\text{C}$. The grey tone indicates increasing amplitude. The horizontal stippled lines indicate levels of significance. Only frequencies lower than 0.4 year^{-1} are shown.

Svalbard MAAT 1912–2010 Wavelet Analysis Morlet Complex Adj10 Nmin250

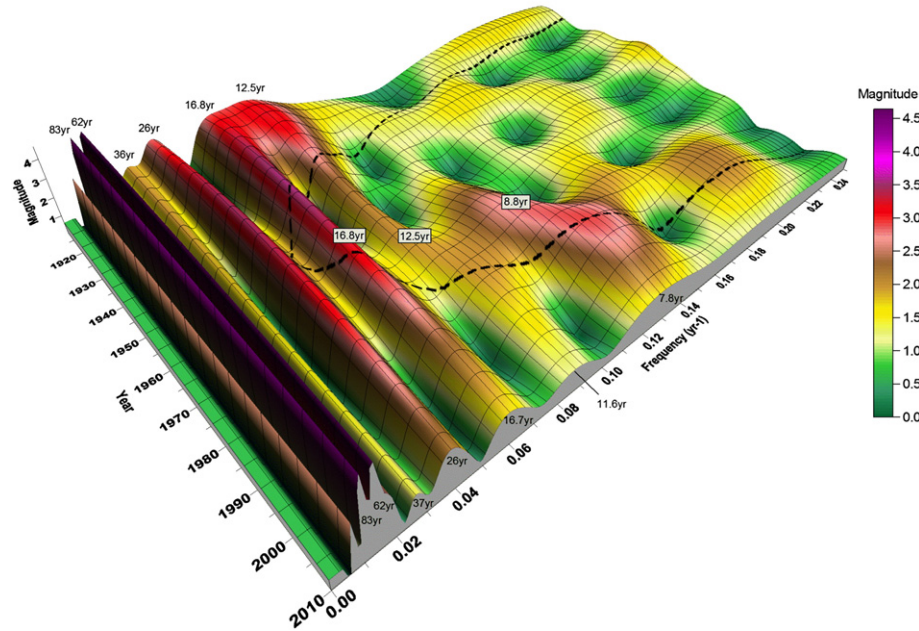


Fig. 3. Diagram showing the continuous wavelet time–frequency spectrum for the Svalbard MAAT series 1912–2010. Time (AD) and frequency (year^{-1}) of cyclic variations embedded in the temperature data are shown along the horizontal axes. Frequencies higher than 0.25 year^{-1} are not shown, corresponding to showing only periods longer than 4 years. The vertical axis (and colour scale) shows the component (magnitude) of the Continuous Wavelet Spectrum at a given time and frequency. Usually the magnitude is 3–4 times the corresponding amplitude. Compare also with Fig. 1, and see main text for further discussion. The magnitude is calculated as $\sqrt{(\text{Re} + \text{Im}) \text{Im}}$, where Re is the real component of a given segment's FFT at a given frequency and Im is the imaginary component. The dotted line indicates the extent of the cone of influence. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

periods may potentially represent sub-harmonics of the about 8.8 year period. When two or more of these variations from time to time peak simultaneously, strong resulting variability may result, which might explain some of the high decadal variability demonstrated by the Svalbard MAAT record.

A physical explanation may be suggested for some of the cycles identified in the Svalbard MAAT series. Apparently the Moon may exercise a regional and global climatic control. The gravitational attraction that the Moon exerts on Earth is the major cause of tides in the oceans, exceeding the influence of the Sun, and the oceanographic tidal flow period is generally synchronised to the orbit of the Moon around Earth. The ocean tidal bulges on Earth are carried ahead of the Earth–Moon axis by a small amount as a result of the Earth's rotation, a consequence of friction and dissipation of energy as water moves over the ocean bottom and into or out of bays and estuaries. Each bulge exerts a small amount of gravitational attraction on the Moon, with the bulge closest to the Moon pulling in a direction slightly forward along the Moon's orbit, because the Earth's rotation has carried the bulge forward. The opposing bulge has the opposite effect, but the closer bulge dominates due to its smaller distance to the Moon. As a result, some of the Earth's rotational momentum is gradually being transferred to the Moon's orbital momentum, and this causes the Moon to slowly recede from Earth at the rate of approximately 38 mm/year. In keeping with the conservation of angular momentum, the Earth's rotation is therefore gradually slowing, and the Earth's day thus lengthens by about 17 ms every year, making each day 1 min longer every 4 million years.

There are, however, a number of cyclic variations in the Moon's orbit around the Earth. One orbital variation relates to the distance between the Moon and the Earth. The distance of closest approach between Moon and Earth is known as *perigee*, whereas the largest distance is known as *apogee*. The line joining these two points is known as the *line of apsides*, and slowly rotates counter clockwise in the plane of the Moon's orbit, making one complete revolution in 8.8504 years, known as the period of recession of *line of apsides*.

Another orbital variation relates to the *line of nodes*. The nodes are the points at which the Moon's orbit crosses the ecliptic plane, defined by the Earth's average orbital motion around the Sun, and the line of nodes is the intersection between these two orbital planes. It has a retrograde motion: seen from Earth it rotates westward along the ecliptic with $19^\circ 21'$ per year, corresponding to a period of 18.5996 years, also known as the period of precession of nodes. At the same time, the Earth's spin axis rotates around the pole of the equatorial plane, because of the tidal forces set up by the Sun and especially the Moon. The resulting slightly irregular axis movement (nudging) is known as the Earth's *nutation*, and follows a predictable cycle on a time scale of less than 300 years. The four dominant periods of *nutation* are cycles of 18.6134 years, 9.3 years, 182.6 days (half-year), and 13.7 days (half-month), but the largest component is the *nutation* cycle of 18.6134 years (Yndestad, 2006), nearly identical to the precession of the Moon's orbital nodes. Both cycles has an approximate period of 18.6 years.

Each of these cyclic variations in the orbit of the Moon and in the orientation of the Earth's spin axis will cause small accelerations and decelerations of the tidal bulges moving around Earth. Much of the energy provided by the Moon's gravitational attraction presumably goes into setting up surface ocean currents that carry water from higher areas of the oceans to lower. The remaining energy may be dissipated by work done in changing ocean volume below the sea surface, influenced by the configuration of the ocean floor (RST, 2011). We hypothesise that this may bring about the emergence of relatively warm or cold water masses from time to time in certain parts of oceans, in concert with these cyclic orbit variations of the Moon, or that these variations may cause small changes in ocean currents transporting heat towards high latitudes, e.g. in the North Atlantic. The resulting variations in sea surface temperature would then influence the temperature of the atmosphere above the oceans (Keeling and Whorf, 1997), whereby there may be a potential link between orbital variations of the Moon and the average global air temperature.

The potential influence of the Moon on air temperatures, if correctly interpreted above, reflects redistribution of energy from the oceans to the atmosphere, and vice versa, and the overall amount of heat in the ocean–atmosphere system may therefore well remain stable. However, by influencing upon air temperatures, there may be derived changes in snow- and sea ice cover, which influences on the surface albedo and the overall planetary surface energy balance. By this the orbital effects of the Moon may also be reflected in the total amount of heat in the ocean–atmosphere system.

Orbital variations of the Moon and the Earth have since long been suggested to influence upon long-period ocean tides, climate cycles, and variations of marine biomasses (Pettersson, 1905, 1914, 1915, 1930). Later Maksimov and Smirnov (1965) and Currie (1981, 1984, 1987) analysed surface temperatures in the North Atlantic, and found temperature cycles close to the 18.6 year lunar nodal cycle. Also Loder and Garret (1978) and Royer (1989, 1993) suggested the existence of an 18.6 year temperature cycle from data obtained along the east and west coast of North America. In addition, the 18.6 year nodal tide has a poleward velocity component (Maksimov and Smirnov, 1967) and amplitude of approximately 7% of the lunar diurnal component (Neuman and Pierson, 1966), which may influence the ocean surface layer and air temperatures at high latitudes (Royer, 1993; Keeling and Whorf, 1997). Yndestad (1999, 2003, 2006) actually was able to identify harmonic and sub-harmonic lunar nodal cycles of $18.6/3 = 6.2$ years, 18.6 , $3 \times 18.6 = 55.8$ years, and $4 \times 18.6 = 74.4$ years in temperature series from the Barents Sea between mainland Norway and Svalbard. Also a third harmonic cycle of the 74 year cycle, or $74.4/3 = 24.5$ years, is often observed in marine data series, as is a shorter cycle period of $24.8/3 = 8.5$ years, corresponding to a third harmonic cycle of the 24 year cycle (Yndestad, 2006).

The 62, 37–36, 26, 16.8 and 8.8 year periods identified by the wavelet analysis (Fig. 3) may potentially all be interpreted as lunar signals. The 8.8 year period is very close to the fundamental 8.8504 year lunar period, also known as the period of recession of *line of apsides*, and the longer periods may represent sub-harmonics of this fundamental period. The 83 year period (Fig. 3) may correspond to the solar Gleissberg cycle (named after Wolfgang Gleißberg), ranging from 50 to 140 years, with a maximum around 88 years (De Jager et al., 2010), corresponding to four times the Hale cycle of 22 years.

Thus, the Svalbard MAAT record appears to include potentially lunar and perhaps also solar signals, at least when considering periodic variations identified in the still relatively short 98 year Svalbard MAAT record. Most of the cycles identified longer than 10 years appear to have an almost stationary cycle length and stationary signal magnitude, while the shorter cycles are less stable and tend to come and go with time (Fig. 3). Several periods identified in the Svalbard MAAT record resembles similar periods observed in Barents Sea surface temperatures (Yndestad, 1999, 2003, 2006), which emphasises that air temperatures in Svalbard presumably are strongly influenced by oceanographic and sea ice conditions in the surrounding region (Benestad et al., 2002).

As the above wavelet analysis show most of the dominant periods to be stationary phenomena (Fig. 3), it is feasible to construct a harmonic or sinusoidal model approximating the original data. The algorithm used for this has three stages. First a Fourier procedure is used to estimate the frequencies and component count. Secondly a linear fit is made to determine the amplitudes and phases. These values represent the starting estimates for the third and final stage, a non-linear optimization. As some of the individual periods identified by the wavelet analysis are slowly changing with time, the chosen sinusoids have to be optimised for frequencies, amplitudes, and phases for the entire period investigated, and may therefore differ somewhat from the modern situation and from the result of the Fourier analysis (Fig. 2). This is parallel to the situation where the result of a linear regression analysis deviates from the last data points in the series

analysed. However, when the strongest cyclic variations remain stable, such as demonstrated by the wavelet analysis of the Svalbard MAAT record (Fig. 3), this does not represent a major problem for the construction of a harmonic model. As always, the coefficient of determination (r^2) and the sample size (N) will together represent a guide for the degree of success of the model optimization.

3.3. Modelling the Svalbard MAAT record 1912–1990

With the general stability of identified periods in mind, we constructed a sinusoidal model to hindcast the original data. First we investigated a truncated 1912–1990 subseries of the original 1912–2010 record, to investigate not only the capacity of hindcasting using this modelling approach, but also to investigate if this modelling approach has forecasting potential, by conducting an out-of-sample test for a period where the result today is known (1991–2010).

When carrying out the non-linear optimization to construct a harmonic or sinusoidal model approximating the original data, it is in principle possible to incorporate any number of periodic variations identified by the wavelet analysis (Fig. 3). However, to keep the analysis simple we decided to take into account only three different periodic variations, as the wavelet analysis suggested a relatively low number of dominant periodic variations to characterise the overall Svalbard MAAT record. In our analysis the not-explained part of the original MAAT data series was considered as random walk (red) noise, and not used for further analysis. Had we instead chosen to incorporate a higher number of periodic variations (Figs. 2 and 3), the hindcasting ability of our model would of course improve. Here our main purpose is however to demonstrate that a low number of periodic variations may explain all main features of the record. The resulting modelled data series were finally retrended to produce a hindcast comparable to the real Svalbard temperatures (Fig. 4).

To investigate the length of the reliable or realistic forecasting time range, if any, we conducted a series of out-of-sample tests where different meteorological data series (not only Svalbard) were truncated stepwise back in time from the last year in the record (2010). From the truncated series we then generated forecasts for the period between the years of truncation to 2010, to compare with the measured data for this period.

Here we show the results of such an out-of-sample exercise on the Svalbard MAAT series 1912–2010 (Fig. 4). The MAAT data series was stepwise truncated from the last year of observation (2010) and new optimised models generated from this reduced data series. The resulting forecast was then compared to the real observations between the year of truncation and 2010. For the Svalbard MAAT series most of the strongest periods identified are stable with regard to both length and strength (Fig. 3), and it was found that by truncating the data series as early as 1990 we were still able to generate a useful forecast for the period 1991–2010 (Fig. 4). The non-linear optimization for the 1912–1990 truncated observational period resulted in a optimised model combining three periods of 71.7, 24.9 and 15.3 years. By this the original data were hindcasted with a coefficient of determination $r^2 = 0.36$ ($N = 78$). For comparison, a linear regression of the same data yielded a coefficient of determination (r^2) of only 0.02.

Our optimised model reproduces all main features displayed by the Svalbard 1912–1990 record, including the rapid early 20th century warming 1915–1920, the warm peak 1930–1940, and another warm period centred on 1955–1957, the subsequent cold period culminating 1967–1968, and increasing temperatures from then until around 2006. In this case, had we made this forecast back in early 1991, the now observed record high temperatures 2005–2007 would have been forecasted from the wavelet analysis, even though at that time there were no indications in this record per se for such a future temperature increase.

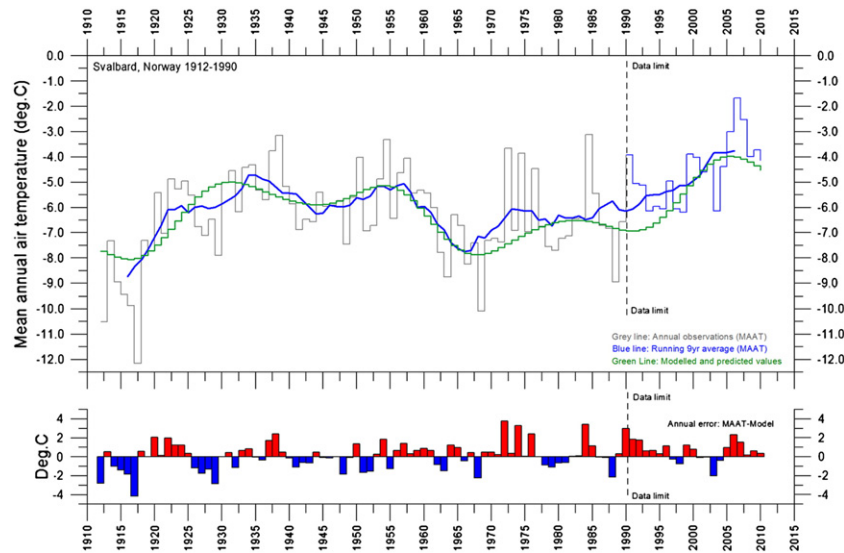


Fig. 4. The truncated Svalbard MAAT series 1912–1990. The grey line shows annual observed values. The thin blue line shows the measured values 1991–2010, which were excluded from analysis. The thick blue line shows the simple running 9 year average of the original data. MAAT values modelled using three cycles only are shown by the green line. The 1991–2010 part of this represents the out-of-sample forecast. The lower panel shows the difference (the model error) between measured and modelled MAAT for each year in the entire observational period. Note that the temperature scales are different in the two panels. The coefficient of determination (r^2) for the hindcasting period is 0.36 ($N = 78$). The overall linear temperature trend 1912–1990 is about 0.099 °C per decade. This overall trend is assumed to continue beyond 1990 when plotting the forecasted data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The forecasted 1991–2010 period represents about 26% of the length of the truncated 1912–1990 Svalbard series. In the lower part of Fig. 4 the annual model error is shown, and there is no major change seen in the error distribution and its magnitude at the truncation year 1990. Errors 1991–2010 remain essentially identically to those characterising the period 1912–1990, with random distribution between positive and negative values. This demonstrates that our three-period only model manages to stay on track in relation to the observed data for the whole period, both before and after 1990. The typical annual model error is 1–4 °C, which for the individual year represents a considerable error. Clearly our model should not be tested (falsified) within such a short time scale, but over several years. The good fit between modelled values and the simple moving 9 year average suggest a forecasting falsification time range of about 9 years for our simple 1912–1990 model, based on only three input periods.

More work on the reliable or useful forecasting time range for this technique is clearly needed. However, our preliminary experience from undertaking out-of-sample tests like the above on different meteorological series, is that the useful forecasting time range typically is 10–25% of the length of the background data series. Time series where the dominant periods vary with regard to length and strength have a relatively short forecasting time range, while series characterised by stable dominant periods (like the Svalbard series) have relatively longer forecasting time ranges.

3.4. Modelling and forecasting using the Svalbard MAAT record 1912–2010

We next moved on to develop an optimised model for the entire 1912–2010 observational period. This resulted in a model combining

the periods of 74.3, 24.5 and 17.1 years (see Table 1 for listing of periods), by which the original data were hindcasted with a coefficient of determination $r^2 = 0.47$ ($N = 98$). For comparison, a linear regression of the same data yielded a coefficient of determination (r^2) of 0.14. It may be noted that the 74.3 year period found and used by the optimised model may be related to the fundamental 18.6 year lunar period ($4 \times 18.6 = 74.4$ years), and that the 24.5 year period is identical to a third harmonic cycle of the 74.4 year cycle ($74.4/3 = 24.8$ years). The 17.1 year optimised period is close to the 16.9–16.7 year period found by the wavelet analysis (Fig. 3). In principle, even the best optimised model may yield results without real physical meaning, but when it is possible to relate known physical phenomena to the results, this in our opinion lends support to the usefulness of the model.

Our simple three-period only optimised model (Fig. 5) reproduces all main features displayed by the Svalbard MAAT record, including the rapid early 20th century warming 1915–1920, the warm peak 1930–1940, another warm period centred on 1955–1957, the subsequent cold period peaking 1967–1968, a warm period 1970–1975, a cold period around 1980, and finally the subsequent warming until 2007.

On an annual basis, errors (lower panel in Fig. 5) between the real and the modelled data are typically 1–3 °C. The somewhat smaller error margin compared to the 1912–1990 analysis is due to the longer data set and the resulting improved determination of periodic signals. The spread of annual errors is seen to be random, and do not show a trend towards dominance of either positive or negative values, demonstrating that the whole record can be described without systematic bias using an input of only three periods.

Table 1

Length of cyclic variations found in the Svalbard 1912–2010 MAAT record by Fourier and wavelet analyses, and period length used for reproducing the MAAT 1912–1990 and 1912–2010 MAAT record with only three input periods, respectively. Parentheses around Fourier values indicate that these variations may possibly represent harmonics of the longer 68.4 year variation. Shaded columns indicate periods used in the models (Figs. 4 and 5).

Cycle length	80–100	50–79	30–49	20–29	15–19	11–14	9–11	8–9
Fourier analysis		68.4	(36.7)	25.7	16.8	(12.3)	10.5	8.7
Wavelet	83	62	36	26	16.8–16.7	12.5–11.6		8.8
Model 1912–1990		71.7		24.9	15.3			
Model 1912–2010		74.3		24.5	17.1			

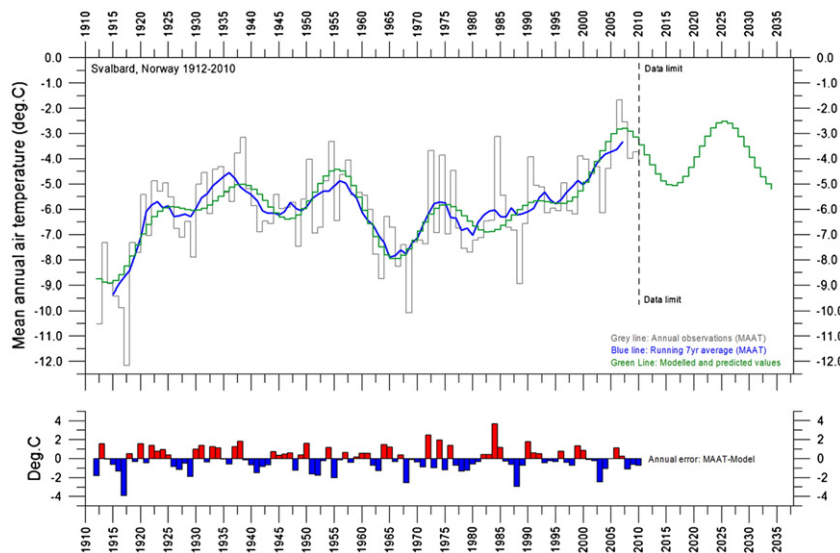


Fig. 5. The Svalbard MAAT series 1912–2010. The grey line shows annual values, and the blue line shows the simple running 7 year average of these original data. MAAT values modelled from three cycles only are shown by the green line. The lower panel shows the annual difference (the model error) between measured and modelled MAAT. Note that the temperature scales are different in the two panels. The coefficient of determination (r^2) for the hindcasting period is 0.47 ($N=98$). The overall linear temperature trend 1912–2010 is about 0.23°C per decade. This overall trend is assumed to continue beyond 2010 when plotting the forecasted data. As mentioned above, this trend may be unrealistic high, being influenced by the data series starting at a low and ending at a high value. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The wavelet analysis of the Svalbard MAAT record (Fig. 3) shows the dominant variations to be stable with respect to strength and magnitude. This suggests that natural variations which are strong now are likely to continue without major changes at least some time into the future, and therefore likely to influence also the future climate. This knowledge on persistent and strong natural variations may be used for an attempt of forecasting, at least some time into the near future. Based on the optimised model for 1912–2010 we then generated a forecast of Svalbard MAAT as shown in the right hand part of Fig. 5. This forecast suggests future MAAT in Svalbard to decline until around 2015–2017, to be followed by a new warming period, peaking around 2026. Following this future temperature peak MAAT again is forecasted to decline. The forecast shown in Fig. 5 is influenced by a perhaps unrealistic high linear trend 1912–2010. Should the real trend beyond 2010 be lower, this would change our forecast towards lower temperatures.

Our forecast suggests that the observed late 20th century warming in Svalbard is not going to continue for the next 20–25 years. Instead the period of warming may be followed by variable, but generally not higher temperatures for at least the next 20–25 years. As our model hindcast 1912–2010 underestimates the interannual variation, but is close to the moving simple 7 year average (Fig. 5), we suggest a falsification time scale of about 7 years. Incorporating additional periods in the model would produce a more detailed forecast and a somewhat shorter falsification time range, but here our main purpose is to demonstrate that all main features of the entire Svalbard MAAT record may be reproduced by combining a few periodic variations only. Table 1 shows all main periods found or used by the above analysis of the Svalbard MAAT record.

4. The GISP2 series

To obtain a longer time perspective, we next considered the reconstructed central Greenland surface temperatures for the past 4000 years, derived from the bidecadal $\delta^{18}\text{O}$ record from the Greenland Ice Sheet Project II (GISP2) ice core (Alley, 2000, 2004). Different paleoclimatic indicators in the GISP2 ice core, and the basis for their transfer functions, have previously been reviewed by Alley (2000) and

will not be discussed here. The last year in the reconstructed GISP2 temperature record is 1855 AD.

The minimum duration of a paleoclimatic event that is directly resolvable by ice core isotope analysis increases with increasing age and decreasing thickness of the individual annual ice layer thickness. The gradual loss of detail with age is indicated by the GISP2 reconstructed temperature data, which comes with a time resolution of about 20 years for data from around 1850 AD, and about 60 years for data about 40,000 years old. For the time interval considered here (until 4000 BP) the effective time resolution therefore is about 20 years. It should also be carried in mind that because the isotopic thermometer measures the temperature difference between moisture source and precipitation site, the correlated changes that likely occurred in temperature at source and site would cause isotopic changes to underestimate the real temperature changes (Boyle, 1997).

First the GISP2 temperature record since 4000 years BP was exposed to a Fourier analysis, after removing a linear trend of -0.0052°C per decade. The result of this is shown in Fig. 6. Five periods of about 3598, 1139, 788, 584 and 366 years long are seen to dominate the record. The peak value of these periods all exceeds the 99.9% critical limit (null hypothesis is white noise), indicating that there is less than a 1 in 1000 probability they arose from chance.

As the Fourier analysis (Fig. 6) suggested the existence of about 10 major oscillations in the data set, we specified a wave number of 10. The wavelet analysis of the reconstructed GISP2 surface temperature record also disclosed the existence of several cyclic variations (Fig. 7). Throughout the last 4000 years a periodicity of about 1130–1170 years has been important. A less well defined cycle of about 3600 years in duration is also found by the wavelet analysis, but is not shown in Fig. 7. In addition to these long variations, shorter cyclic variations with periods of about 790–770 and 590–560 years have also been prominent during the last 4000 years. The 790 year variation has been decreasing since 4000 years BP, and is not important in modern times. The existence of the about 1130 and 560 year periods is interesting because $1130 \sim 2 \times 560$ years. At times when these periods are nearly in phase, pronounced temperature peaks roughly about 1100 years apart will dominate the GISP2 record. A fourth period of about 360–390 years long was important in the early part of the GISP2 record considered, but has since weakened,

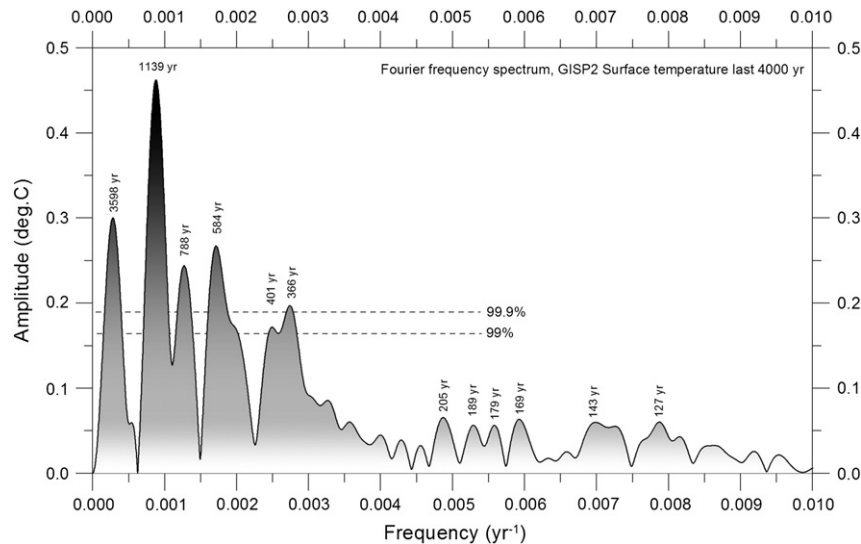


Fig. 6. Fourier analysis (using Best Exact N composite algorithm) of the detrended GISP2 surface temperature series. The record is dominated by periods of about 3598, 1139, 788, 584 and 366 years long, all with amplitude greater than 0.2 °C. The grey tone indicates increasing amplitude. The horizontal stippled lines indicate levels of significance. Only frequencies lower than 0.01 are shown.

and has all but disappeared today. The dominant periodic variations of 1130, 790–770, 560 and 390–360 years identified by the wavelet analysis in the GISP2 record (Fig. 7) may all be represented in the Fourier spectrum by the 1139, 788, 584 and 366 year peaks (Fig. 6).

We were not able to identify a cyclic variation with a period length of about 1470 years in the GISP2 data since 4000 years BP, although northern hemisphere Holocene climate has been proposed to be characterised by such a cyclic variation (see, e.g., Bond et al., 1997, 2001). Schulz (2002a, 2002b), however, found the 1470 year cycle to be associated solely with the occurrence of Dansgaard–Oeschger interstadial events 5, 6, and 7 during the Weichselian glaciation, that is, between 32,000 and 35,000 years BP.

In addition to the above long cyclic variations we also identified a number of shorter variations. Most notable are variations with period length of about 205, 175 and 130 years are present in the data, although the magnitude of none of these variations has been strong or stable over the time considered. Most of these periods are also recognised by the Fourier spectrum analysis (Fig. 6). The difference in record length and time resolution between the GISP2 record and the Svalbard MAAT series explains why many of the periodic variations found in the Svalbard series are not apparent in the GISP2 series, and vice versa.

As mentioned previously, the attribution of physical explanations for the observed cyclic climate change is not our main concern.

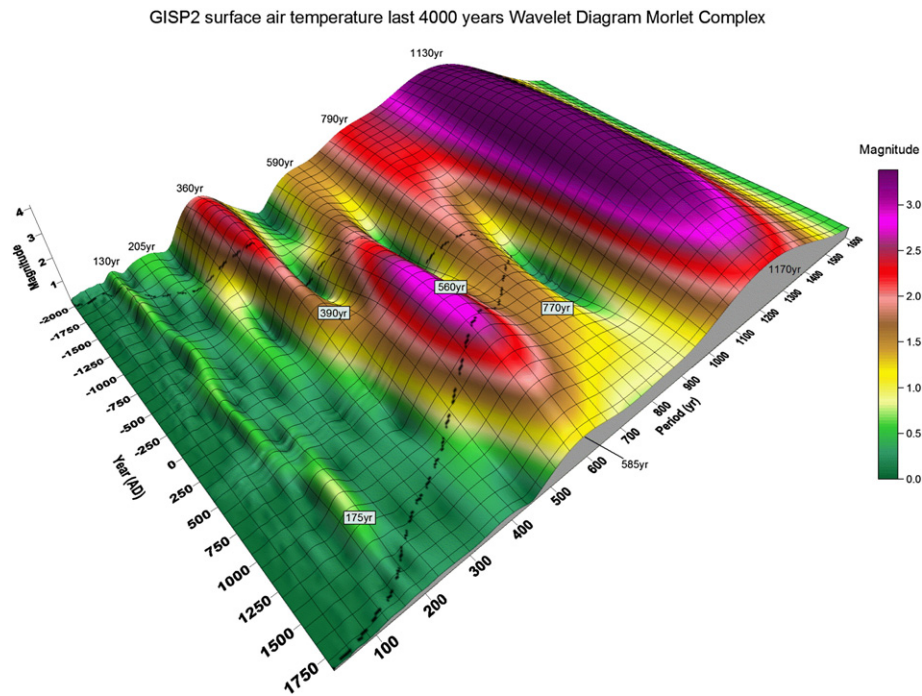


Fig. 7. Diagram showing the continuous wavelet time–frequency spectrum for the GISP2 reconstructed surface temperature for the past 4000 years. Time (AD) and period length (years) of cyclic variations embedded in the temperature data are shown along the horizontal axes. The vertical axis (and colour scale) shows the magnitude of these variations. The discordance around year 400 AD is due to a data discontinuity. To ensure good visual resolution of long periods, the analysis result is plotted against period length, and not against frequency (as in Fig. 3). The dotted line indicates the extent of the cone of influence. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

However, the causes of long (millennial scale) climate changes are generally poorly understood, and the issue is important for understanding the natural climate variability, as illustrated by ice and ocean cores. Also the lack of a CO₂ cycle at millennial time scales underscores the independence of such long climate variability from anthropogenic greenhouse enhancement (Alley, 2003).

Evidence for important climatic cyclicity of about 500 and 1000 years long has previously been suggested from other data types. Stuiver et al. (1995) studied the ¹⁸O/¹⁶O ratios in the GISP2 core, and found evidence for a 530 year cyclicity, which tentatively was ascribed to solar influence. In East Africa Stager et al. (1997) found evidence for a 510 year period in the diatom assemblages in a sediment core from Lake Victoria. Studying Holocene North Atlantic circulation patterns Chapman and Shackleton (2000) found evidence of cyclic variations about 550 and 1000 year long. By applying a 300 year running mean filter to the Holocene GISP2 $\delta^{18}\text{O}$ record Schulz and Paul (2002) found a distinct low-frequency component with a periodicity of about 900 years. Vasiliev and Dergachev (2002) carried out power spectrum, time–spectrum and bispectrum analyses of the long-term series of the radiocarbon concentrations derived from measurements of the radiocarbon content in tree rings over the last 8000 years. They noted an important period of about 2400 years long, which they ascribed to potential solar forcing. Also Mordvinov and Kramynin (2010) found evidence for a solar period of about this length (2300 years). By harmonic analysis of the radiocarbon time series Vasiliev and Dergachev (2002) described a number of shorter periods, about 940, 500, 210 and 190 years in length. From a statistical study of tree ring index values, Zhou and Butler (1998) noted a cyclic component with a period of about 200 years, which they related to solar variation. From a study of solar and terrestrial components of the atmospheric ¹⁴C variation and the radiocarbon evidence for low frequency solar oscillation, Damon and Sonett (1992) and Damon and Jiraković (1992) concluded that the 2400 and 210 year periods should be considered as fundamental solar cyclic variations. De Jager et al. (2010) list the De Vries cycle of 205 years and the Hallstatt cycle of ~2300 years as important solar cycles. However, the cause(s) for the above mentioned Holocene climate variations still remain a topic for debate. In general, hypotheses regarding their origin include internal oscillations of the climate system (e.g. Schulz and Paul, 2002), external forces like variations in the Sun's radiative output (e.g., Bond et al., 1997, 2001) and combinations of the two.

We infer that the about 1130 and 590–560 year periods identified by us in the GISP2 core (Fig. 7) may correspond to the about 1000 and 500 year periods identified by all the above studies. The 205 year cycle may correspond to the Suess or De Vries cycle of solar activity (Garcin et al., 2006), and the 189 period identified by the Fourier analysis may be identical to the 190 year solar induced variation found by Vasiliev and Dergachev (2002).

Most of the dominant variations identified by the wavelet analysis are persistent with respect to strength and magnitude (Fig. 7). For the entire 4000 year period of the GISP2 record we therefore constructed a mathematical model based on only three periods: 2804, 1186 and 556 years, all found by non-linear optimization, as described previously for Svalbard. Table 2 shows all main periods found or used by the GISP2 analysis. Using the crude three-period only approach we

were nevertheless able to hindcast all main features of the original GISP2 temperature series (Fig. 8), with a coefficient of determination $r^2 = 0.63$. As can be seen from Fig. 8, the timing of historical warm periods like the Medieval Warm Period, the Roman Warm Period and the Minoan Warm Period are all reproduced by our simple natural cycle model, as are intervening cold periods such as the Dark Age and the Little Ice Age (LIA). The main discrepancy is the lack of replication of a medium sized warming around 3–400 AD, which is apparent in the GISP2 data. Had we instead included more than only three periods in our analysis, we would have been able to reproduce more details of the original GISP2 record, including the 3–400 AD warm period, but here our main purpose is to demonstrate that by combining only a small number of periodic variations it is possible to reproduce all main features of the record. This suggests that also the long-term climatic development as displayed by the GISP2 data is controlled by a relatively small number of fundamental cycles.

The hindcasting ability demonstrated by this approach motivates an attempt to use the optimised natural cycle model to forecast main features of the near-future Central Greenland mean annual air temperature (Fig. 8). As mentioned above, the GISP2 temperature record ends 1855 AD, before onset of the 20th century warming. It turns out that the natural cycle approach based on wavelet analysis is able to forecast the observed 1856–2010 warming (Fig. 8) as an out-of-sample forecasting test. The forecasted period (155 years) represents about 4% of the total length of the background data series (4000 years).

It should here be emphasised that Central Greenland temperature changes are not identical to global temperature changes. However, they do tend to reflect planetary temperature changes with a decadal-scale delay (Brox et al., 2009), with the notable exception of the Antarctic region and adjoining regions in the southern hemisphere, which is more or less in opposite phase (Chylek et al., 2010) for variations shorter than Ice-Age cycles (Alley, 2003).

The warming following the Little Ice Age is generally perceived as a natural recovery from the previously cold period, and the effect of anthropogenic greenhouse enhancement is assumed to become important only after 1975 (IPCC, 2007). Our simple cyclic model (Fig. 8) is able to forecast the main features of this recorded warming until 2010, underlining that a significant part of the 20th century warming may be interpreted as the result of natural climatic variations, known to characterise at least the previous 4000 years. As the shortest period used in our modelling is 556 years, the time resolution of the model is correspondingly coarse. Had we included more than just three periods, the modelled post Little Ice Age warming would have been more pronounced, reaching about the same level as during the Medieval Period. Moreover, even in the absence of anthropogenic greenhouse enhancement our natural cycle forecast for central Greenland suggests a continuation of the present warm period for most of the 21st century. After that the overall late Holocene cooling trend may again dominate, driven by orbitally induced gradual reduction of solar insolation at high latitudes, but this future development being dependent upon the magnitude of the anthropogenic greenhouse enhancement.

5. Conclusions

- (1) This study has identified several persistent cyclic variations in climatic and meteorological records from Svalbard and

Table 2
Length of cyclic variations found in the GISP2 surface temperature record since 4000 BP by Fourier and wavelet analyses, and period length used for reproducing the record by three input periods only. Parentheses around Fourier values indicate that these variations may possibly represent harmonics of the longer 1139 year variation. Shaded columns indicate periods used in the model (Fig. 8).

Cycle length	2000–4000	1000–1999	600–999	400–600	300–399	200–299	150–199	100–149	50–99
Fourier analysis	3598	1139	788	(584)	(366)	205	189, 179, 168	143, 127	79, 58
Wavelet	3500	1170–1130	790–770	590–560	390–360	205	175	130	
3-period model	2804	1186		556					

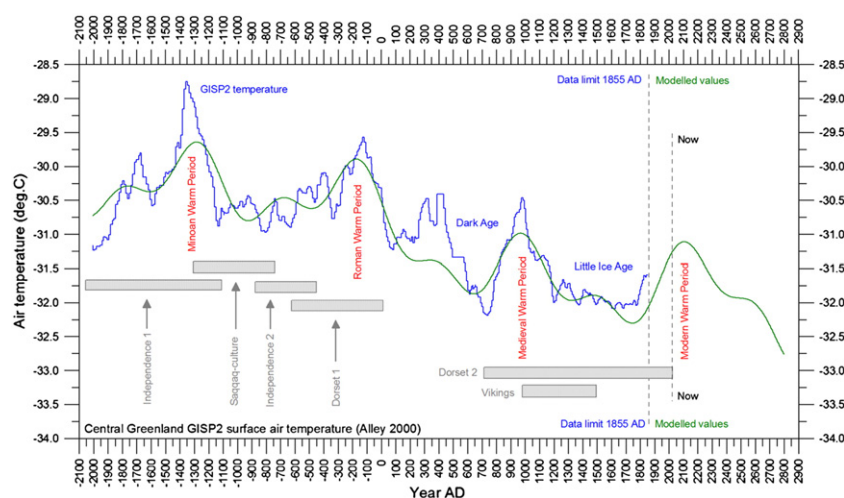


Fig. 8. Central Greenland (GISP2) surface temperature the past 4000 years (blue line). Natural cycle modelled and forecasted data are shown by the green line. The coefficient of determination (r^2) for the hindcasting period is 0.63. The timing of certain historical warm periods in Europe is shown by red text, and the timing of Greenland cultures are shown in grey. The overall declining linear temperature trend during the last 4000 years is $-0.0052\text{ }^{\circ}\text{C}$ per decade, and is assumed to continue when plotting the forecasted data beyond 1855. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Greenland. Some of the cycles appear to correspond to known cyclic variations in the Moons' orbit around Earth, while others may correspond to solar variations. Notwithstanding the physical explanation for such cyclic variations, which is not the main focus of the present study, wavelet analysis of climatic and meteorological records represents a potentially useful means for climate analysis, as a supplement to Fourier analysis. In contrast to Fourier analysis, the wavelet analysis provides information on the time-dependant dynamics of observed recurrent climate variations, which is especially important to understand the physical explanation for observed variations and to evaluate the future development.

- (2) The present warm period following the Little Ice Age since about 1800 AD can be reproduced by a simple three input period only approach, based on the Greenland GISP2 temperature record. Apparently the present period of warming since the LIA to a high degree may be the result of natural climatic variations, known to characterise at least the previous 4000 years.
- (3) Both investigated records show high natural variability and exhibits long-term persistence, although on different time scales. The strength and persistence of several of the identified natural cyclic variations suggests that a natural cycle based forecasting of future climate may be potentially feasible, at least for limited time ranges. Our empirical experience suggests a realistic forecasting time range of about 10–25% of the total record length. In the case of Greenland, such forecasting suggests that the present post LIA warm period is likely to continue for most of the 21st century, before the overall Late Holocene cooling may again dominate, but this being dependant on the magnitude of the anthropogenic greenhouse enhancement.
- (4) Fourier and wavelet analyses deconstruct data series into their fundamental components. Natural cycles that have remained strong over several decades or centuries are likely to continue without major changes into at least the near future, and will therefore be essential for forecasting any future climatic development. Forecasts based on insights obtained by Fourier and wavelet analyses should therefore not be considered purely statistical, as they are based on observed dynamics characterising past climate change. Used together, Fourier and wavelet analyses represent potential important techniques for climate analysis.

- (5) The natural cycle climate model forecast described in the present paper is supplementary to forecasts (scenarios) derived from analytic climate models, and thereby represents a complimentary approach to climate forecasting based on such analytic models.

Acknowledgements

The present study was carried out partly at the University of Oslo, and partly at the University Centre in Svalbard (UNIS). The Greenland GISP2 data were obtained from the NOAA Ice Core Gateway (<http://www.ncdc.noaa.gov/paleo/icecore/greenland/greenland.html>). The Wavelets package AutoSignal v.1.7 by SeaSolve Software Inc. was used for data analysis.

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