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Time-scales of the European surface air temperature variability: The role of the 7–8 year cycle

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Air temperature variability on different time scales exhibits recurring patterns and quasi-oscillatory phenomena. Climate oscillations with the period about 7–8 years have been observed in many instrumental records in Europe. Although these oscillations are weak if considering their amplitude, they might have non-negligible influence on temperature variability on shorter time scales due to cross-scale interactions recently observed by Paluš [Phys. Rev. Lett. 112, 078702, (2014)]. In order to quantify the cross-scale influence we propose a simple conditional mean approach which estimates the effect of the cycle with the period close to eight years on the amplitude of the annual cycle in surface air temperature (SAT) in the range 0.7–1.4 °C and the effect on the overall variability of the SAT anomalies (SATA) leads to the changes 1.5–1.7 °C in the annual SATA means. The strongest effect in the winter SATA means reaches 4–5 °C in central European station and reanalysis data.

Key points

The effect of cross-scale interactions in air temperature variability is quantified

7-8 year cycle influences the amplitude of the annual cycle in Europe

7-8 year cycle influences inter-annual variability of air temperature anomalies

1. Introduction

The Earth climate, in general, and the air temperature, in particular, vary on many spatial and temporal scales. We will focus on a relatively small temporal range from the annual scale to near-decadal time scales, in long-term surface air temperature (SAT) records from the European midlatitudes. Long instrumental temperature records available from a number of European stations give a unique opportunity to study the long-term temperature variability and to identify repeating patterns such as inter-annual climate oscillations. Analyzing the 335-year-long central England temperature (CET) record, *Plaut et al.* [1995] identified climate oscillations with the period about 7–8 years. *Baliunas et al.* [1997] and *Benner* [1999] have confirmed this finding in CET, while *Paluš and Novotná* [1998] detected an oscillatory phenomenon in the same frequency range in the 223-year-long SAT record from Prague-Klementinum, as well as in SAT from other European locations, e.g. De Bilt, Berlin, Wroclaw [*Paluš and Novotná*, 2004]. *Pišoft et al.* [2004] and *Brázdil et al.* [2012] observed the 7–8 year cycle in SAT from various stations in the Czech Republic. *Grieser et al.* [2002] reported the 7–8 year oscillations in SAT records from western and northern Europe and *Pišoft et al.* [2009] identified spatial patterns of occurrence of the 8-year cycle at various geopotential levels in the NCEP/NCAR reanalyzed temperature series. *Sen and Ogrin* [2015] extended this list using SAT from Zagreb, while *Čermák et al.* [2014] detected the 7–8 year cycle in soil and ground temperatures collected in the Prague Geothermal Climate Change Observatory. The 7–8 year oscillations have also been observed in various climate-related data in Europe, the North Atlantic and the Mediterranean regions (see, e.g. *Gámiz-Fortis et al.* [2002], *Kondrashov et al.* [2005], *Feliks et al.* [2010]). These cycles have usually been observed using subtle detection techniques such as the singular spectrum analysis (SSA) [*Vautard et al.*, 1992], Monte Carlo SSA [*Allen and Smith*, 1996], or Enhanced MC SSA [*Paluš and Novotná*, 1998, 2004] since their amplitude is typically very low and the cycles, e.g., in the air temperature, are hidden in the overall temperature variability. For example, in our estimates, described below, the amplitude of the cycle with the period about 8 years (the red curve in Figs. 1a, b), extracted from the Prague-Klementinum SAT record, is smaller than 0.5 °C. We can observe, however, approximately 8-year modulation of the amplitude of the annual cycle (the blue curve) and of the winter minima (Fig. 1a, SAT data in grey) in markedly greater ranges. Therefore it is important to understand possible relations between slow cycles and faster temperature variability.

Studying interactions between dynamics on various time scales in long-term daily SAT records from European locations, *Paluš* [2014] has observed an information transfer from larger to smaller time scales in the form of a causal influence (causality in the Granger sense, see [*Hlaváčková-Schindler et al.*, 2007]) of the phase of slow temperature oscillations on the amplitude of faster temperature variability. The influenced faster variability is characterized by the temporal scales from a few months to 4–5 years, while the periods of the influencing oscillatory phenomenon vary between 6 and 11 years, however, the most probable period is between 7 and 8 years (see Fig. 3a in [*Paluš*, 2014].)

In this letter we propose an approach to quantify the effect of the cross-scale influence of the oscillatory mode with the period close to 8 years on the amplitude of the annual temperature cycle, as well as on the overall variability of SAT anomalies (SATA) in Europe. We will show that this

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effect is non-stationary, variable in space and time, however, it is non-negligible and significantly larger than the amplitude of the 7–8 year cycle itself. Therefore this phenomenon requires further research and understanding of its mechanisms and assessment of potential predictability skills related to interannual temperature variability.

2. Data and Methods

2.1. Data

Daily mean SAT data recorded at several stations with sufficiently long uninterrupted record provided by the ECA&D project (*Klein Tank et al.* [2002]) were used for the study of temporal evolution of the effect of the cross-scale interactions in the temperature variability. Results from Prague - Klementinum (longitude 14° 25' E, latitude 50° 05' N), which record spans the period 1775/1/1 – 2013/12/31 are presented here. Results from two German stations: Hamburg - Fuhlsbüttel (9° 59' E, 53° 38' N) with the record spanning 1891/1/1 – 2013/12/31 and Potsdam (13° 04' E, 52° 23' N) with the record spanning 1893/1/1 – 2013/12/31 are presented in the supporting information.

For the study of the spatial variability of the effect over Europe, the temperature reanalysis data from E-OBS dataset from the EU-FP6 project ENSEMBLES provided by the ECA&D project (*Haylock et al.* [2008]) were used. The dataset has daily temporal and 0.25° × 0.25° spatial resolution. The spatial domain is confined to the range from 35° N to 65° N and from 12.5° W to 40° E. The temporal domain spans the period of 1950/1/1 - 2013/12/31.

2.2. Methods

We use the raw SAT data when the variability of the annual cycle is studied. The SAT anomalies (SATA), obtained from the SAT data by subtracting the average annual cycle (see the supporting information for details) are used for analyses of the variability on all other temporal scales (overall variability thereafter).

An oscillatory signal $s(t)$ can be conveniently described using its instantaneous amplitude $A(t)$ and phase $\phi(t)$. A broadband signal recorded from a multiscale process needs to be filtered into a spectral band of interest. In this study, both the filtering and amplitude and phase estimation is performed using the continuous complex wavelet transform (CCWT) with the Morlet mother-wavelet [*Torrence and Compo*, 1998] which provides the instantaneous amplitude $A_f(t)$ and the instantaneous phase $\phi_f(t)$ for each wavelet central frequency f. Details and other approaches are described, e.g., by *Paluš et al.* [2005].

The instantaneous phase of the oscillations with the period close to 8 years is estimated from daily (station or reanalysis) SATA data using the CCWT with the central wavelet frequency corresponding to the period 8 years. The same method using the central wavelet period of 1 year is also used to extract the instantaneous phase and amplitude of the annual cycle from the SAT data. As the continuous wavelet transform results in a redundant decomposition, the real part $A_f(t) \cdot \cos\phi_f(t)$ of the wavelet component representing the annual cycle is regressed to fit the SAT data in order to interpret the amplitude values in °C.

Conditional means of either the amplitude of the annual cycle or the overall SATA variability, conditioned on the phase of the 8-year cycle, are computed using a simple binning technique. The phase interval $(-\pi, \pi)$ (representing the full cycle) is divided into 8 bins. For each bin we evaluate the mean (or standard deviation) and obtain a discretized estimate of the conditional mean of the studied variable. See the supporting information for details. If the 8-year cycle has no influence on the studied variable, the conditional means in all 8 bins should be the same, equal to the unconditional, global mean. Or, due to the finite sample effect, the conditional means should randomly fluctuate around the unconditional mean. If the conditional means vary as a function of the phase of the 8-year cycle, we will use the difference between the maximum and minimum conditional mean as a measure of the effect of the 8-year cycle on the studied variable. The statistical significance of such an effect is evaluated using the surrogate data method. The Fourier transform (FT) surrogate data [*Theiler et al.*, 1992] represent a null hypothesis of a process with the same power spectrum as the studied data, but without any cross-frequency interaction. The rejection of this null hypothesis provides a statistical evidence for a cross-scale effect of the 8-year cycle on temperature variability on shorter time scales. See the supporting information for details and other surrogate data types.

3. Amplitude of the annual cycle in SAT

The strongest mode of variability in the European temperature data is the annual cycle. Its amplitude, however, varies in time and space, see, e.g., [*Zveryaev*, 2007]. The wavelet reconstruction $\psi_{1y}(t) = A_{1y}(t) \cdot \cos\phi_{1y}(t)$ (the black curve in Fig. 1a), regressed to match the SAT data (grey) is plotted in Fig. 1a along with the amplitude $A_{1y}(t)$ of the annual cycle (blue) and the reconstruction $\psi_{8y}(t) = A_{8y}(t) \cdot \cos\phi_{8y}(t)$ (red) of the 8-year cycle.

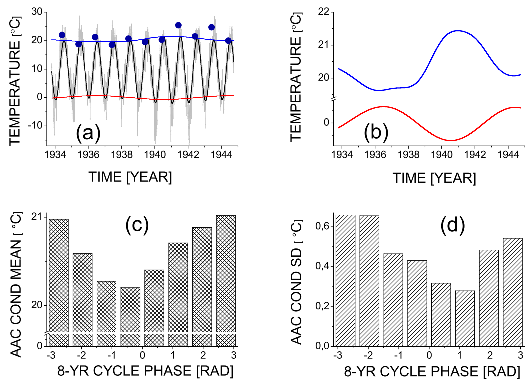

Figure 1. (a) Cycles in the SAT data in the period 1933/10/20 - 1944/10/01. Shown are the SAT daily station data from Prague-Klementinum (grey), the wavelet reconstruction $A_{8y}(t) \cdot \cos\phi_{8y}(t)$ of the 8-year cycle (red), the wavelet reconstruction of the annual cycle $A_{1y}(t) \cdot \cos\phi_{1y}(t)$ (black), the wavelet amplitude $A_{1y}(t)$ of the annual cycle (blue) and the climatological amplitude (dark-blue dots, see the supporting information for details). (b) The wavelet reconstruction of the 8-year cycle (red) and the wavelet amplitude of the annual cycle (blue) "zoomed" in their individual scales. (c) Conditional means, and (d) conditional standard deviations (SD) for the amplitude of the annual cycle, $A_{1y}(t)$, for the Prague-Klementinum SAT data within the period 1962/1/1 - 2009/12/31, conditioned on the phase $\phi_{8y}(t)$ of the 8-year cycle, divided into 8 equidistant bins. Note that each bin represents approximately one year of the 8-year cycle.

A "climatological amplitude" (dark blue dots in Fig. 1a), defined as the difference between the means of daily temperatures above the upper quartile and below the lower quartile in each year, is in a good agreement with the amplitude $A_{1y}(t)$ acquired from the wavelet transform.

The apparent relationship (visually enhanced using individual scales in Fig. 1b) between the amplitude of the annual cycle (AAC thereafter) and the 8-year cycle (Pearson correlation coefficient -0.86) is further studied using the conditional mean technique, conditioning the AAC $A_{1y}(t)$ means on the phase $\phi_{8y}(t)$ of the 8-year cycle. The histogram of the conditional means of the AAC is presented in Fig. 1c. The maximum mean, conditioned on the phase of the 8-year cycle, is located in the eighth bin at 21.02 °C, while the minimum is located in the fourth bin at 20.20 °C. This implies that through the 8-year cycle, the AAC changes, on average, within the range of 0.82 °C. The conditional standard deviations of the AAC are ranging from 0.28 to 0.66 °C with higher values in the outer bins and lower values in the central bins (Fig. 1d).

The change 0.82 °C of the AAC within the 8-year cycle is the average change for the 6 cycles in the period 1962/1/1 - 2009/12/31. When using different segments of the data, the results differ due to non-stationarity of the temperature data and their cross-scale interactions. In order to depict this nonstationarity, the temporal evolution of the difference between the maximum and minimum conditional means was characterized using the sliding window of 16384 daily SAT samples (Fig. 2). In the 239-year-long Prague-Klementinum record the differences range from 0.2 to 1.3 °C and they are statistically significant mainly during the last 90 years. The long-term evolution of the AAC variability reflects a modulation on the scale 60–80 years (Fig. 2). This is the scale of the Atlantic Multidecadal Oscillation which influences large-scale climate variability modes [*Wyatt et al.*, 2012], and SAT variability on global [*Chylek et al.*, 2014a] and regional [*Chylek et al.*, 2014b] scales. However, inclusion of the multidecadal scales into the study of the cross-scale interactions is left for future research.

The gridded temperature reanalysis data on the dense 0.25° × 0.25° spatial grid underwent the same AAC conditional means analysis using the phase of the CCWT-extracted 8-year cycle. The areas with the statistically significant maximum differences of the AAC conditional means are marked by the hatch pattern in Fig. 3. The marked influence of the phase of the 8-year oscillatory mode on the amplitude of the annual cycle can be seen over central, northern and eastern Europe.

4. Overall SATA variability in the 8-year cycle

Above we have examined the effect of the 8-year cycle on the amplitude of the annual cycle. Since the 8-year cycle has an effect on various temporal scales [*Paluš*, 2014], now we explore its effect on the overall variability represented by the surface air temperature anomalies. Again the conditional mean technique with the 8 phase bins is used and the results for the SATA data from Prague-Klementinum are presented in Fig. 4. The conditional SATA means, conditioned on the phase of the 8-year cycle (Fig. 4a) show that negative temperature anomalies ("cold bins") prevail at the beginning and the end of the 8-year cycle (with the minimum -0.79 °C in the first bin), while the positive anomalies ("warm bins") dominate the middle of the cycle (with the warmest bin having 0.72 °C anomaly). The conditional standard deviations (Fig. 4b) are behaving in the opposite way.

The difference between the maximum and minimum SATA conditional means, i.e., the effect of the 8-year cycle on the SATA variability, is approximately 1.5 °C. This value exceeds the 98th percentile of the related surrogate data distribution (Fig. 4c), i.e., it is statistically significant

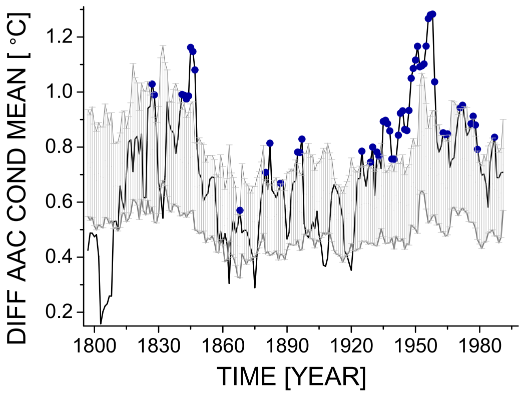

Figure 2. Temporal evolution of the effect of the 8-year cycle on the amplitude of the annual cycle in the Prague-Klementinum daily SAT. The differences between the maximum and minimum AAC conditional means (black curve), tested using 1000 FT surrogates (the means plotted as the grey curve, the 95th percentile of the surrogate distribution is plotted using the light grey curve, connected by the grey bars with the surrogate means). Windows with statistically significant differences are marked by the blue dots, plotted in the middle of the window of the effective length 36.86 yr (see the supporting information for details).

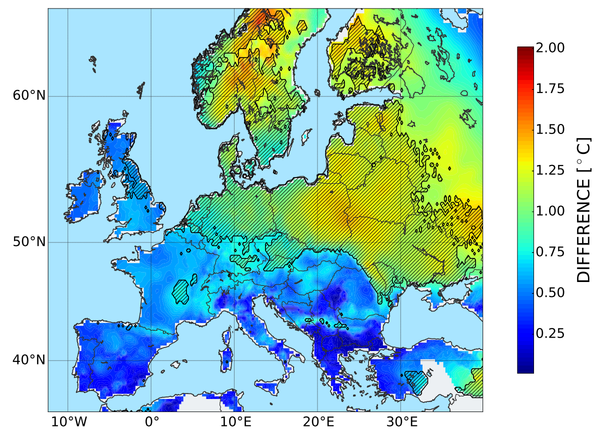

Figure 3. Spatial variability of the effect of the 8-year cycle on the amplitude of the SAT annual cycle in Europe. Differences of the maximum and minimum conditional means of the ECA&D reanalysis SAT annual cycle amplitude, $A_{1y}(\mathbf{x}, t)$, conditioned on the phase of the 8-year cycle, $\phi_{8y}(\mathbf{x}, t)$. The hatch pattern marks the areas where the effect is statistically significant.

with $p < 0.02$. The amplitude of the 8-year cycle, estimated from the SATA data, is less than 0.5 °C and is well reproduced in the FT surrogate data (Fig. 4d). These computational statistics (Figs. 4c, d) support the hypothesis that the 1.5 °C difference in the SATA conditional means is not a result of random variability, neither can be explained by an 8-year component, linearly added to a background variability. Since the amplitude of the 8-year cycle itself is smaller than 0.5 °C, the difference 1.5 °C of the annual means during the 8-year cycle is mainly the result of the cross-scale interactions of the 8-year cycle with the variability on shorter time scales.

The effect of the 8-year cycle on the overall SATA variability, similarly as its effect on the amplitude of the annual cycle, varies in time and space. It also differs when we consider different seasons. The strongest effect was observed for the winter (DJF) season, when the differences between the maximum and minimum mean winter temperature, conditioned on the phase of the 8-year cycle, reach approximately 4–5 °C in the station SATA data from central Europe. During the summer season the effect is not statistically significant, i.e., it is not distinguishable from random variability. See the supporting information for details.

The spatial variability of the effect on the winter temperature in Europe, estimated from from the ECA&D SATA data, is presented in Fig. 5. The areas with the statistically significant maximum differences of the conditional SATA means in the DJF season are marked by the hatch pattern. The differences range from about 1 °C in Spain to the maximum of 6.5 °C in Finland and adjacent areas of Russia. The pattern is similar to that in Fig. 3 and in central and eastern Europe they both resemble (the inverse of) the mountain topography: the effect of the 8-year cycle is strong in the lowlands from the North and Baltic seas southward and weakens at the mountain ranges of Alps and Carpathians. The interaction of variable jet stream with the mountain topography apparently has a modulating effect on the influence of the 8-year cycle on the temperature variability in Europe.

5. Discussion and Conclusions

Considering air temperature variability in a range of time scales, *Paluš* [2014] presented a statistical evidence for a cross-scale directed information flow from larger to smaller time scales in long-term SAT records from European stations. The phase of a slow oscillatory process influences temperature variability on shorter time scales. The influencing oscillatory phenomenon has variable frequency, however, its most probable period is close to 8 years and for this period it has also the strongest effect (see Figs. 2b and 3a in [*Paluš*, 2014]). These periods (time scales) are consistent with the observations of an oscillatory mode with the period between 7 and 8 years in long-term temperature and other meteorological records in Europe (see the references in Introduction). Therefore, in this study we have applied a simple conditional mean technique in order to quantitatively estimate the effect of the oscillatory mode with the period close to 8 years on the surface air temperature variability in Europe. The cycle itself has a small amplitude (< 0.5°C in the presented example of the station SAT record from Prague-Klementinum, see Fig. 4d) and is hidden in overall temperature variability. However, due to the cross-scale interactions [*Paluš*, 2014], the 8-year cycle influences the temperature variability on shorter time scales. The amplitude of the annual cycle in SAT changes within this cycle by 0.7–1.4 °C and the overall variability of SAT anomalies changes in annual means by 1.5–1.7 °C. The strongest effect of the 8-year cycle has been observed in the winter season – the DJF SATA means change in the range 4–5 °C. (This summary is restricted to 20th-century central Europe, where we have available both the station and reanalysis data giving consistent results.) These results suggest that the weak 7–8 year

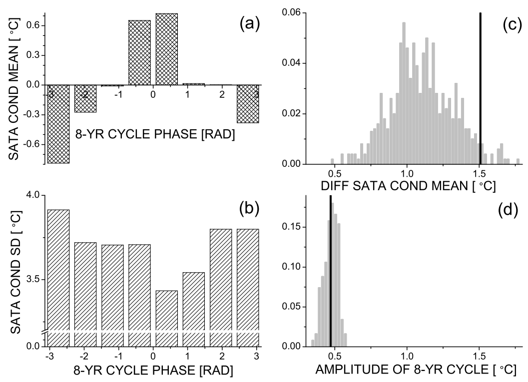

Figure 4. (a) Conditional means and (b) conditional standard deviations for the daily SATA from Prague-Klementinum in the period 1962/1/1 - 2009/12/31 conditioned on the phase of the 8-year cycle, $\phi_{8y}(t)$. (c) The difference between the maximum and minimum SATA conditional means depicted by the position of the black bar (≈ 1.5°C) and the distribution of the same differences obtained from 1000 realizations of the FT surrogate data (grey histogram). (d) The mean amplitude of the 8-year cycle depicted by the position of the black bar (< 0.5°C) and the distribution of the mean amplitudes of the 8-year cycles obtained from 1000 realizations of the FT surrogate data (grey histogram).

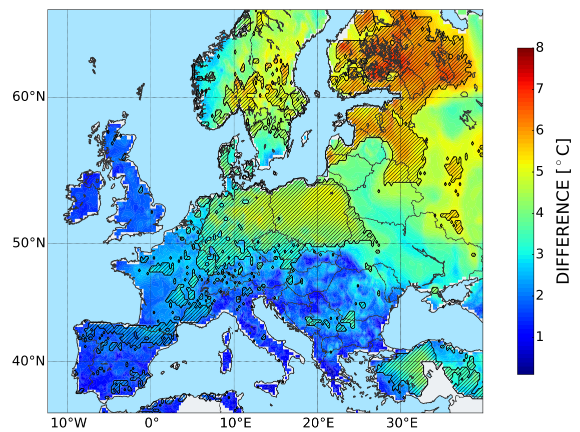

Figure 5. Spatial variability of the effect of the 8-year cycle on the mean winter temperature in Europe. Differences of the maximum and minimum conditional DJF means of the ECA&D reanalysis SATA, conditioned on the phase of the 8-year cycle, $\phi_{8y}(\mathbf{x}, t)$. The hatch pattern marks the areas where the effect is statistically significant.

cycle plays a very important role in the temperature variability on inter-annual and shorter time scales. Therefore this phenomenon deserves further study and understanding of its mechanisms.

Paluš [2014] hypothesizes that in the analyzed SAT data we have observed a regional manifestation of a general phenomenon of cross-scale interactions in the atmospheric dynamics in which global, low-frequency modes influence local, high-frequency variability. For instance, *Chekroun et al.* [2011] reported that the phase of the low-frequency modes of the El Niño-Southern Oscillation influences high-frequency variability ("weather noise") of the sea-surface temperature in the tropical Pacific. For the data analyzed in this study, the most relevant global mode is probably the North Atlantic Oscillation (NAO). The influence of the NAO on the air temperature in Europe is known [*Marshall et al.*, 2001] and its mechanisms depending on the phase of the NAO are described, e.g., by *Hurrell and Dickson* [2005]. Typically, Pearson's correlations have been computed between (mostly winter) air temperature records and NAO indices (see, e.g., *Pokorná and Huth* [2015]), however, specific time scales have not been considered yet, although the 7–8 year cycle has also been detected in the NAO index [*Gámiz-Fortis et al.*, 2002; *Paluš and Novotná*, 2004]. Our results demonstrate the importance of understanding of the climate variability in scale-specific regional modes and their cross-scale interactions and causal relations with global circulation variability modes which are localized not only in space [*Vejmelka et al.*, 2014], but also in a time scale or in a frequency range [*Groth and Ghil*, 2011, 2015].

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