

## Statistics of the seasonal cycle of the 1951-2000 surface temperature records in Italy

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**Summary.** — We present an analysis of seasonal cycle of the last 50 years of records of surface temperature in Italy. We consider two data sets which synthesize the surface temperature fields of Northern and Southern Italy. Such data sets consist of records of daily maximum and minimum temperature. We compute the best estimate of the seasonal cycle of the variables considered by adopting the cyclograms' technique. We observe that in general the minimum temperature cycle lags behind the maximum temperature cycle, and that the cycles of the Southern Italy temperatures records lag behind the corresponding cycles referring to Northern Italy. All seasonal cycles lag considerably behind the solar cycle. The amplitude and phase of the seasonal cycles do not show any statistically significant trend in the time interval considered.

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### 1. – Introduction

The analysis of the seasonal cycle of temperature records is of the uttermost importance in order to provide a detailed description of the climate of the geographical area under consideration. A correct approach to the evaluation of the seasonal signal allows to have a clearer picture of changes in such a signal and at the same time permits a more precise position of the problem of estimating the statistical properties, in terms of short-time variability, long-term trend, and extremes, of the residual signal.

In particular, the possibility of capturing with greater detail the properties of the seasonal signal is especially relevant for the analysis of regions, like the Mediterranean area, that are characterized by relevant intermittence. The presence of noticeable year-to-year variations for the seasonal cycle in the Italian peninsula has been observed and

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reported in some of the most relevant treatises of the past, from the Roman Age—in Plinius the Old’s *Naturalis Historia*—to early XIX century—in Leopardi’s *Zibaldone*.

In this study we analyze the seasonal cycle for a 50-year period (1951-2000) of the maximum and minimum temperature records of two synthetic stations series, which synthesize the information regarding Northern and Southern Italy. The data have been derived from daily observations of temperatures taken in 64 stations covering the Italian peninsula.

In order to provide the statistical description of the seasonal signal of any record, able to quantify the *mean* seasonal cycle and as well as the properties of its *short-* and *long-term variability*, we must have several, well-defined sampled estimates of its fundamental characteristics, namely *phase* and *amplitude*.

In these terms, the application of the Discrete Fourier Transform (henceforth, DFT) on the entire record is of relatively little use, since it provides only the best—in terms of fraction of the total variance—*global* estimate of the phase and amplitude of the  $1\text{ y}^{-1}$  frequency component, while no information is given on the variability of the seasonal cycle.

For each record, we estimate the seasonal component throughout the record by considering the collection of all the *local* (in time) best estimate of seasonal cycle. Such an approach is along the lines of the statistical technique proposed when introducing the cyclograms [1, 2]. The resulting seasonal signal is not precisely periodic, since the phase and the amplitude of the computed sinusoidal curve are not constant. Therefore it is possible to statistically analyze how the amplitude and phase of the seasonal signal vary with time.

Such an approach is viable because our data obey with the narrow-band approximation, *i.e.* in each subset of the data used for the local estimates, the spectrum of the data has a sharp, narrow peak for the  $1\text{ y}^{-1}$  frequency component, so that the phase and amplitude of the seasonal cycle are well defined.

We wish to underline that very recently sophisticated DFT-based techniques, which follow a different approach than ours, have been proposed to assess simultaneously the diurnal, seasonal and long-term variability of climate records [3].

Our paper is organized as follows. In sect. **2** we describe the data sets considered in this work. In sect. **3** we describe how it is possible to analyze a given frequency component of a signal by considering a collection of its local estimates. In sect. **4** we present the analysis of the seasonal cycles of the data. In sect. **5** we present an analysis of the significativity of the trends of the estimated phase and amplitude of the seasonal signals. In sect. **6** we present the analysis of the de-seasonalized data. In sect. **7** we present our conclusions.

## 2. – Data description

The data used in this study are derived from a set of station records with daily minimum and maximum temperature observations for a 50-year period (1951-2000). They were extracted from the Italian Air Force (Aeronautica Militare, henceforth AM) climatic database, that was recently used for the study of Italian daily precipitation [4, 5]; cloud cover [6] and sea level pressure [7] as well. The AM climatic database includes 164 stations. Some of them, however, cover only rather short periods, other ones have a large number of missing data. Since we are interested in providing information on the Italian climatology, we have selected a subset of the stations which give a reasonable coverage of Italy and which are provided with long and reliable records. The result was a subset

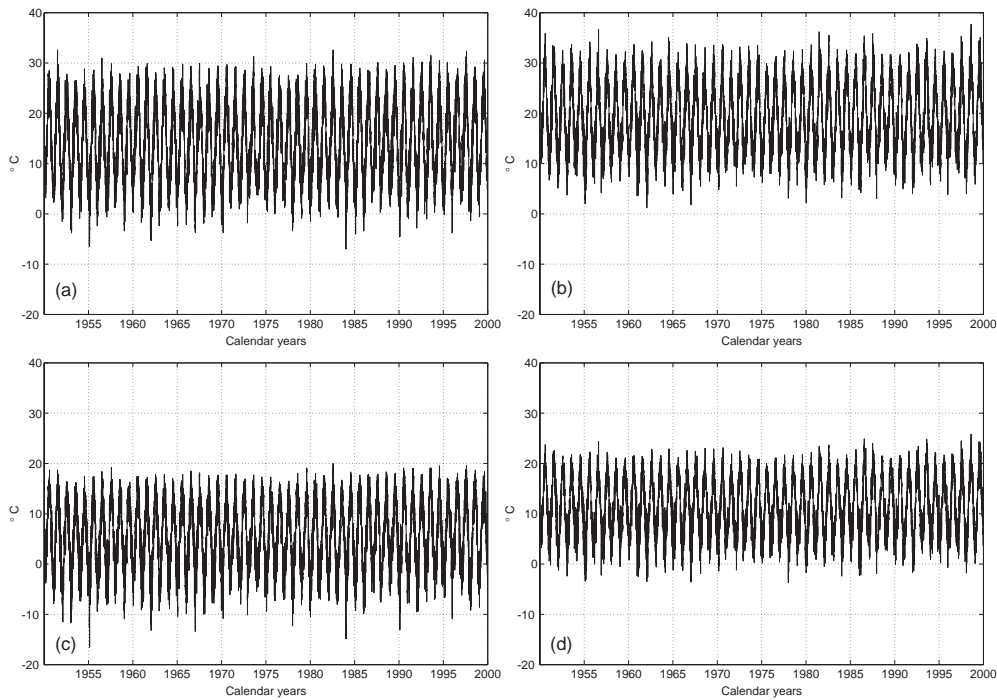


Fig. 1. – Maximum and minimum temperature records of station N and station S: a) station N maximum temperature; b) station S maximum temperature; c) station N minimum temperature; d) station S minimum temperature.

of 64 stations. The selected records were quality-checked and in order to increase the confidence of the results, homogenization was based, not only on AM records, but also on records derived from other data sources such as Ufficio Centrale di Ecologia Agraria, Servizio Idrografico, and some specific research project that allowed daily series to be recovered for several of the most important Italian observatories.

EOF analysis, which will be fully reported in a future publication, shows that the daily maximum and minimum temperature data fields can be reduced with a good degree of approximation to two degrees of freedom. In both cases, these degrees of freedom contribute to over 90% of the variance of the signal. The first two principal components are representative of the two geographically distinct areas of Northern and Southern Italy. Therefore, it has been possible to create two synthetic data sets for Northern and Southern Italy, which henceforth we refer to as station N and station S temperature records, respectively. Each of the 64 stations has been assigned to either station N or station S on the basis of a score. Then the station N and station S synthetic data sets have been created by suitably averaging the data of the corresponding stations. Each resulting data set consists of the records of daily maximum and minimum temperature, which are henceforth indicated as  $T_{\max}^{N/S}$  and  $T_{\min}^{N/S}$ , with obvious meaning of the indexes. These data are depicted in fig. 1. Qualitatively, the geographic boundary dividing the stations contributing respectively to the station N and S data sets is along the parallel between Firenze (Tuscany) and Bologna (Emilia Romagna).

### 3. – Local estimate of a given frequency component

We consider the statistical approach related to the technique of cyclograms [1, 2]. Such an approach provides the possibility of capturing the amplitude and phase time-dependent variations of a given frequency sine wave component of the signal under examination [8, 9].

Given a signal  $x(t)$ ,  $t = 1, \dots, N$ , a frequency  $2\pi/\tau$  and a time window  $2T + 1$ , we consider the centered moving average over  $2T + 1$  terms of the series  $\{x(t) \exp[-i2\pi t/\tau]\}$ :

$$(1) \quad a(t; \tau, T) = \frac{1}{2T + 1} \sum_{j=t-T}^{t+T} x(j) \exp[-i2\pi j/\tau],$$

where  $T + 1 \leq t \leq N - T$  since the signal has  $N$  samplings.

If the frequency  $2\pi/\tau$  is an integer multiple of  $2\pi/N$ , we have that  $a(t; \tau, T)$  can be expressed as the DFT of a suitably convolution product:

$$(2) \quad a(t; \tau, T) = \frac{N}{2T + 1} \text{DFT}[x * w](2\pi/\tau),$$

where the first factor is a renormalization constant,  $*$  represents the convolution product, and  $w$  is the weighting function:

$$(3) \quad w(t) = \begin{cases} \frac{1}{2T + 1}, & 1 \leq t \leq T + 1, \\ 0, & T + 2 \leq t \leq N - T, \\ \frac{1}{2T + 1}, & N - T + 1 \leq t \leq N. \end{cases}$$

Equations (1), (2) imply that, if  $2\pi/\tau$  belongs to the discrete spectrum of the signal, and if  $2T + 1 \geq \tau$ ,  $a(t; \tau, T)$  is related to the best estimate of the  $2\pi/\tau$  frequency sine  $S(t, 2\pi/\tau)$  and cosine  $C(t, 2\pi/\tau)$  wave components of the portion  $t - T \leq t \leq t + T$  of the signal  $x(t)$  as follows:

$$(4) \quad C(t, 2\pi/\tau) = \frac{2}{2T + 1} \text{Re}[a(t; \tau, T)],$$

$$(5) \quad S(t, 2\pi/\tau) = -\frac{2}{2T + 1} \text{Im}[a(t; \tau, T)],$$

where Re and Im indicate the real and imaginary part, respectively. Therefore, we can construct a *global* best estimate of the  $2\pi/\tau$  frequency signal  $\Sigma(t, 2\pi/\tau)$  for each value of  $T + 1 \leq t \leq N - T$  by considering all the *local* best estimates obtained using the result contained in eq. (4):

$$(6) \quad \begin{aligned} \Sigma(t, 2\pi/\tau) &= C(t, 2\pi/\tau) \cos(2\pi t/\tau) + S(t, 2\pi/\tau) \sin(2\pi t/\tau) \\ &= A(t, 2\pi/\tau) \cos(2\pi t/\tau + \phi(t, 2\pi/\tau)), \end{aligned}$$

TABLE I. – *Statistical analysis of the amplitude of the seasonal cycle of the 4 variables considered. Estimated trends are not statistically significant and the values are indicated between brackets.*

Variable	$\langle \text{Variable} \rangle$	$2\sigma(\text{Variable})$	Estimated trend	$2\sigma_{\text{trend}}$
$A \{T_{\max}^N\}$	10.19 °C	1.3 °C	[0.002°C/y]	0.02 °C/y
$A \{T_{\max}^S\}$	8.79 °C	1.3 °C	[0.006°C/y]	0.02 °C/y
$A \{T_{\min}^N\}$	8.65 °C	1.3 °C	[0.004°C/y]	0.02 °C/y
$A \{T_{\min}^S\}$	7.33 °C	1.3 °C	[0.010°C/y]	0.02 °C/y

where

$$(7) \quad A(t, 2\pi/\tau) = \sqrt{C(t, 2\pi/\tau)^2 + S(t, 2\pi/\tau)^2},$$

$$(8) \quad \phi(t, 2\pi/\tau) = -\arctan \left[ \frac{S(t, 2\pi/\tau)}{C(t, 2\pi/\tau)} \right].$$

We can reasonably extend the function  $\Sigma(t, 2\pi/\tau)$  to the whole range  $t = 1, \dots, N$  in the following way:

$$(9) \quad \bar{\Sigma}(t, 2\pi/\tau) = \begin{cases} A(T+1, 2\pi/\tau) \cos(2\pi t/\tau + \phi(T+1, 2\pi/\tau)), & t < T+1, \\ \Sigma(t, 2\pi/\tau), & T+1 \leq t \leq N-T, \\ A(N-T, 2\pi/\tau) \cos(2\pi t/\tau + \phi(N-T, 2\pi/\tau)), & t > N-T. \end{cases}$$

Since the coefficients of the sine and cosine waves change with  $t$ , the signal  $\bar{\Sigma}(t, 2\pi/\tau)$  is not purely periodic, *i.e.* its DFT does not have  $2\pi/\tau$  as only nonzero component. Obviously, the more persistent with  $t$  are the phase and amplitude of the local estimates of the  $2\pi/\tau$  signal, the more monochromatic is  $\bar{\Sigma}(t, 2\pi/\tau)$ .

Phase cyclograms [1,2] provide a very synthetic way of picturing the phase variations of the selected frequency components of the signals. The  $x$ - and  $y$ -components of the phase cyclogram of a signal can be constructed in the following way:

$$(10) \quad PHX(t, 2\pi/\tau) = \sum_{j=1}^t C(j, 2\pi/\tau) / A(j, 2\pi/\tau),$$

$$(11) \quad PHY(t, 2\pi/\tau) = \sum_{j=1}^t S(j, 2\pi/\tau) / A(j, 2\pi/\tau).$$

The more coherent in phase is the frequency component of the signal under examination, the more similar is the resulting graph to a straight line. In the limiting case of a purely periodic signal we actually obtain a straight line, whose angle with the horizontal axis is the phase of the signal, apart from a constant.

#### 4. – Seasonal cycles

In order to apply the techniques presented in the previous section to the temperature records  $T_{\max}^N$ ,  $T_{\max}^S$ ,  $T_{\min}^N$ , and  $T_{\min}^S$ , we have performed a light preprocessing procedure

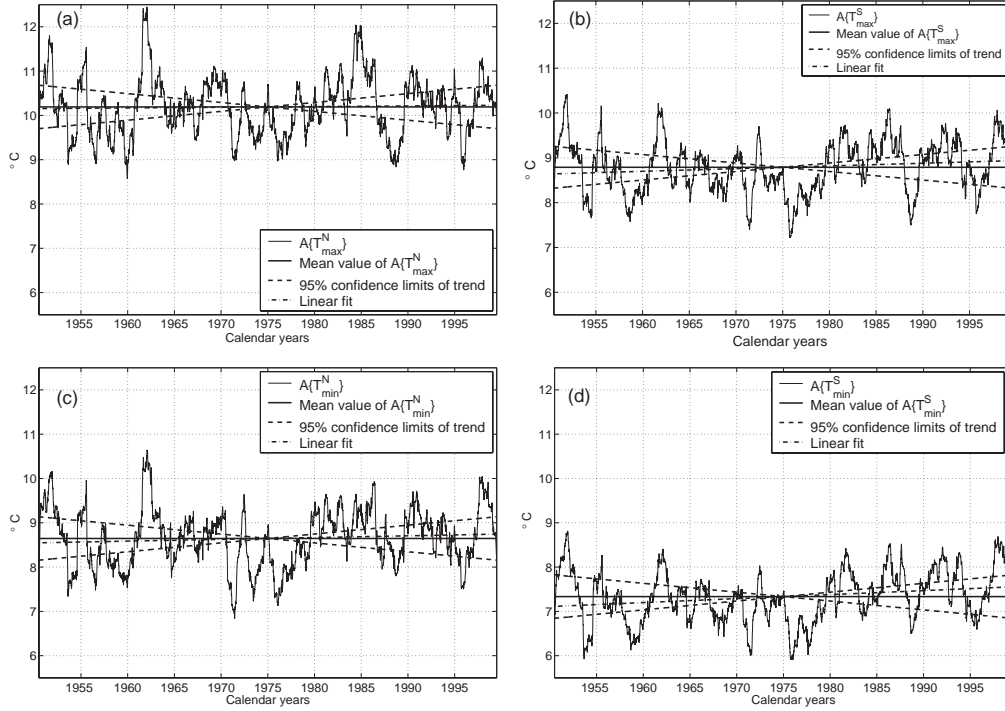


Fig. 2. – Amplitude of the seasonal cycle of the maximum and minimum temperature records of station N and station S: a) station N maximum temperature; b) station S maximum temperature; c) station N minimum temperature; d) station S minimum temperature.

to the data. First of all, the four records presented few missing data, ranging from a minimum of 3 ( $T_{\max}^N$ ) to a maximum of 5 ( $T_{\max}^S$ ). We have filled the holes with simple linear interpolations. Moreover, in order to homogenize the length of the years, we have suppressed the additional data of February occurring in each of the 12 bissextile years of the time frame considered. Since these corrections regard in each case less than 0.1% of the total record, we are confident that this procedure does not alter relevantly the results later presented.

Since we are interested in evaluating the seasonal cycle, we consider in eq. (6)  $\tau = \tau_0 = 365$ . The most natural time window suitable for having a local estimate of the seasonal cycle is clearly one year as well. Therefore, we select  $2T + 1 = 2T_0 + 1 = \tau_0 = 365$ . This choice for  $2T + 1$  implies that, following eq. (1), we have  $49 \times 365 + 1$  local estimates of the seasonal cycle.

It is important to underline that such an approach is sensitive only if the signal obeys the narrow-band approximation, *i.e.* the spectrum of the signal has a strong, narrow peak for the annual cyclic component. If, on the contrary, the signal were characterized by a broad spectral feature comprising the  $1 \text{ y}^{-1}$  frequency component, it would be a mathematical nonsense to investigate whether the seasonal cycle is changing. In such a case the seasonal cycle is just *not defined*, because several contiguous spectral components having different frequencies and shifting phase differences give contributions of comparable importance.

The results we obtain for the amplitude signals are summarized in table I and depicted

TABLE II. – Statistical analysis of the phase of the seasonal cycle of the 4 variables considered. Estimated trends are not statistically significant and the values are indicated between brackets.

Variable	$\langle \text{Variable} \rangle$	$2\sigma(\text{Variable})$	Estimated trend	$2\sigma_{\text{trend}}$
$\Delta\phi\{T_{\text{max}}^{\text{N}}\}$	28 d	8 d	$[-0.03 \text{ d y}^{-1}]$	$0.13 \text{ d y}^{-1}$
$\Delta\phi\{T_{\text{max}}^{\text{S}}\}$	32 d	7 d	$[0.01 \text{ d y}^{-1}]$	$0.09 \text{ d y}^{-1}$
$\Delta\phi\{T_{\text{min}}^{\text{N}}\}$	38 d	7 d	$[0.005 \text{ d y}^{-1}]$	$0.09 \text{ d y}^{-1}$
$\Delta\phi\{T_{\text{min}}^{\text{S}}\}$	42 d	7 d	$[0.01 \text{ d y}^{-1}]$	$0.09 \text{ d y}^{-1}$

in fig. 2. In table II and fig. 3 we report the results referring to the phase signals by indicating, instead of the actual phase delay expressed in radians, the relative delay with respect to the solar forcing expressed in calendar days. We indicate this function as  $\Delta\phi\{T_{\text{max/min}}^{\text{N/S}}\}$ . In fig. 4 we present the results obtained for the function  $\bar{\Sigma}(t, 2\pi/\tau_0)$  for the four records considered.

The first result we want to point out is that there is no statistically significant linear trend in either the amplitude of the phase of the seasonal signal. In other terms, our analysis suggests that in Italy in the time frame 1951-2000 *seasons have not changed* in their annual evolution. The statistical analysis of the trend of the signals is described

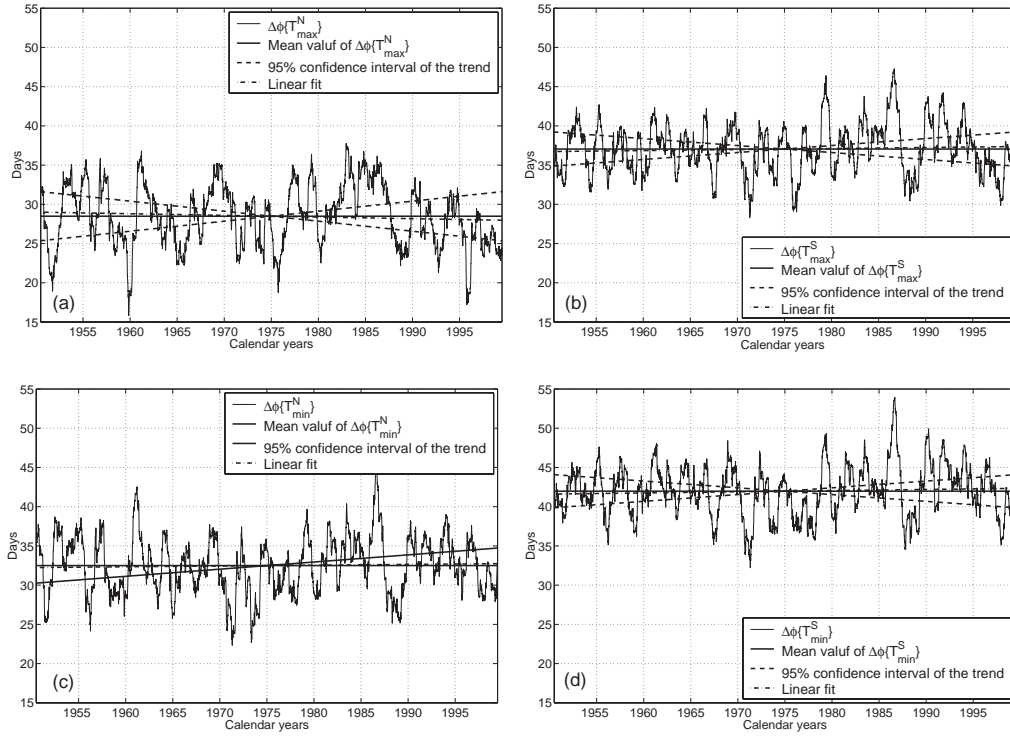


Fig. 3. – Phase of the seasonal cycle of the maximum and minimum temperature records of station N and station S: a) station N maximum temperature; b) station S maximum temperature; c) station N minimum temperature; d) station S minimum temperature.

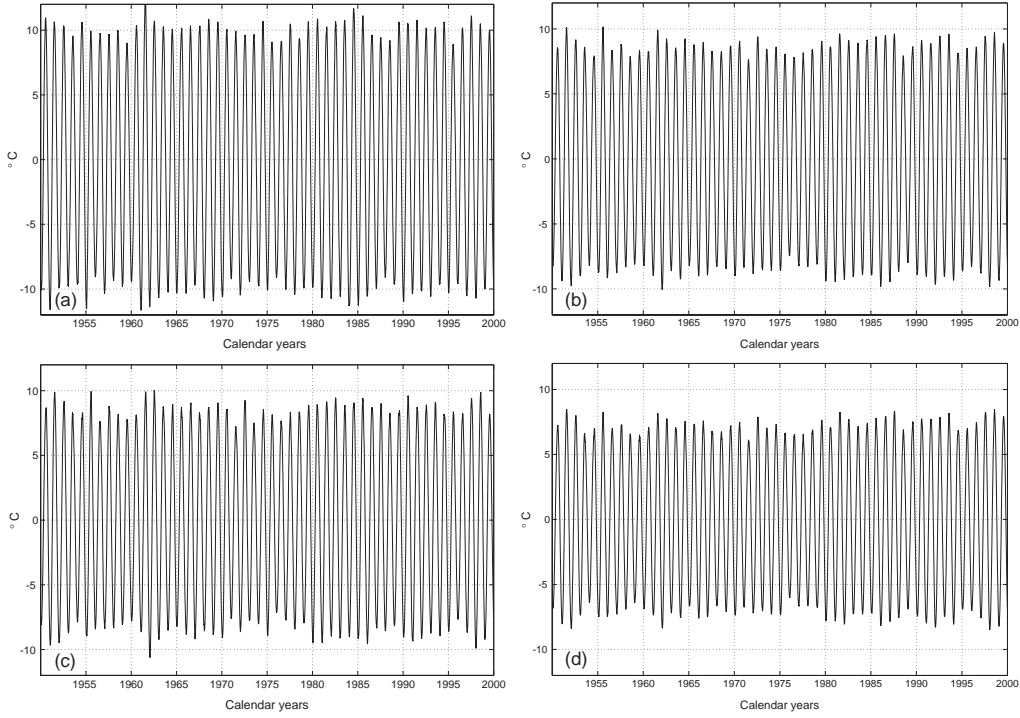


Fig. 4. – Seasonal cycle of the maximum and minimum temperature records of station N and station S: a)  $\overline{\Sigma}(t, 2\pi/\tau_0) \{T_{\max}^N\}$ ; b)  $\overline{\Sigma}(t, 2\pi/\tau_0) \{T_{\max}^S\}$ ; c)  $\overline{\Sigma}(t, 2\pi/\tau_0) \{T_{\min}^N\}$ ; d)  $\overline{\Sigma}(t, 2\pi/\tau_0) \{T_{\min}^S\}$ .

in detail in a later subsection. We underline that in general it is sensible to perform the analysis of the time-dependence of the seasonal signal properties only if the record comprises several seasonal cycles. In our case such condition is obeyed, since we have  $N \gg 2T_0 + 1$ .

The second result we wish to emphasize is that the amplitude of the seasonal signal is significantly larger for maximum than for minimum temperature, and that is significantly larger for variables referring to Northern Italy. Moreover, the two effects roughly sum up linearly, *i.e.*

$$(12) \quad \langle A \{T_{\max}^N\} \rangle - \langle A \{T_{\max}^S\} \rangle \approx \langle A \{T_{\min}^N\} \rangle - \langle A \{T_{\min}^S\} \rangle,$$

where we have dropped the  $t$ - and  $\tau$ -dependences of  $A$  for sake of simplicity and where the notation  $\langle \rangle$  indicates the mean value. Another interesting result is that for both N and S stations the seasonal signal of minimum temperature has an average phase delay with respect to the seasonal signal of the maximum temperature. Moreover, the seasonal cycle of the temperature records of station S has a delay with respect to the seasonal cycle of the corresponding temperature records of station N. Also in this case the two



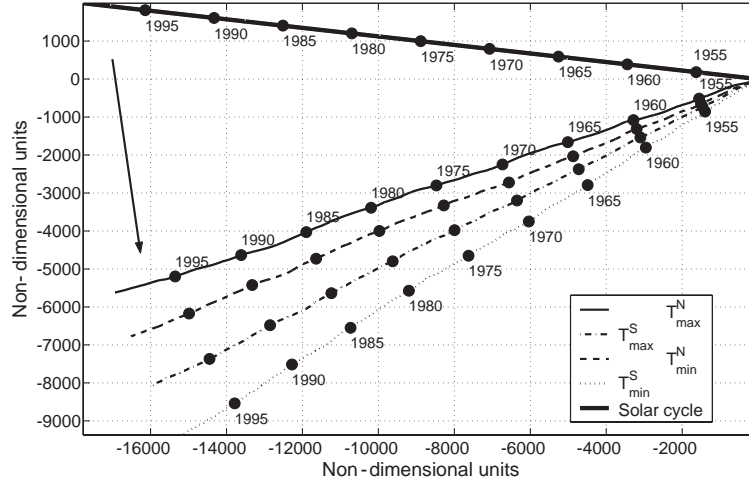


Fig. 5. – Phase cyclograms of the various temperature records and of the solar cycle. Abscissae: cumulative sum of the cosinusoidal coefficients. Ordinates: cumulative sum of the sinusoidal coefficients. The corresponding calendar years are indicated. The arrow points to the angle of increasing phase delay.

effect roughly sum up linearly:

$$(13) \quad \langle \Delta\phi \{T_{\max}^N\} \rangle - \langle \Delta\phi \{T_{\max}^S\} \rangle \approx \langle \Delta\phi \{T_{\min}^N\} \rangle - \langle \Delta\phi \{T_{\min}^S\} \rangle \approx 10 \text{ d},$$

$$(14) \quad \langle \Delta\phi \{T_{\max}^N\} \rangle - \langle \Delta\phi \{T_{\min}^N\} \rangle \approx \langle \Delta\phi \{T_{\max}^S\} \rangle - \langle \Delta\phi \{T_{\min}^S\} \rangle \approx 4 \text{ d},$$

where we have expressed the phase differences in terms of calendar days  $d$ . The maximum temperature record of station N is the closest in terms of phase delay to the solar cycle, which constitutes a fundamental forcing to the system. Such delay corresponds to  $\approx 28$  d.

We present in fig. 5 the cyclograms of the four signals  $T_{\max}^N$ ,  $T_{\max}^S$ ,  $T_{\min}^N$ , and  $T_{\min}^S$ . In the same figure we report the phase cyclogram that can be constructed from the rigorously periodic solar cycle signal, which can be expressed as follows:

$$(15) \quad SC(t) = \cos(2\pi/\tau_0 t + \phi),$$

where  $\phi$  is such that for  $t = 171$  (corresponding to June 21st) the argument of the cosine function is 0. We observe that in all four cases of the temperature data sets the cyclograms are almost indistinguishable from straight lines, since the  $t$ -dependent phase functions are essentially stationary. The above-mentioned average phase differences are the angles—measured counterclockwise—between the best straight line estimates of the cyclograms considered.

We can interpret these results in physical terms as follows. On the one side, the lag and different amplitudes of the cycles of maximum and minimum temperatures can be related to the different impacts of changes of the two well-distinct processes of day solar short-wave heating and night long-wave cooling on the local thermodynamic systems where measurements are taken, in terms of relations to the thermal inertia. On the other side, larger-scale thermal inertia effects related to the different thermal properties of sea and land provide a qualitative argument for the differences in amplitude and phase of the

TABLE III. – *Statistical analysis of the de-seasonalized signal obtained with the cyclograms approach as compared to the results obtained with a conventional DFT approach.*

Variable	$\langle \text{Variable} \rangle$	$2\sigma(\text{Variable})$	$2\sigma(\text{Variable})[\text{DFT}]$
$T_{\max}^N - \overline{\Sigma} \{T_{\max}^N\}$	14.5 °C	5.7 °C	5.9 °C
$T_{\max}^S - \overline{\Sigma} \{T_{\max}^S\}$	19.5 °C	4.8 °C	4.9 °C
$T_{\min}^N - \overline{\Sigma} \{T_{\min}^N\}$	5.7 °C	5.3 °C	5.4 °C
$T_{\min}^S - \overline{\Sigma} \{T_{\min}^S\}$	11.4 °C	4.2 °C	4.3 °C

station N and S cycles, the main reason being that Northern Italy is more continental than Southern Italy.

### 5. – Estimation of the significativity of the trends

We have followed a Monte Carlo approach in order to assess the significativity of the computed trends for both the seasonal cycle amplitude  $A(t, 2\pi/\tau_0)$  and phase  $\phi(t, 2\pi/\tau_0)$  of the four temperature records analyzed.

Our procedure consists in adopting a null-hypothesis, so that we assume that the considered quantity is a stationary autoregressive signal of order  $n$ , which can in general be expressed as

$$(16) \quad w(t) = m + \sum_{k=1}^n c_k w(t-k) + \eta(t),$$

where  $\eta$  is a white spectrum noise with variance  $\sigma_\eta$ . We estimate for the considered quantity the optimal order  $n$ , as well as the optimal values of the relevant parameters  $m$ ,  $\{c_k\}$ , and  $\sigma_\eta$  of the corresponding autoregressive process (16). This can be performed, *e.g.*, using a suitable MATLAB<sup>®</sup> routine [10,11]. We wish to emphasize that the routine in [10,11] allows to estimate the optimal  $n$  with either Schwarz's Bayesian criterion [12] (henceforth, SBC) or the logarithm of Akaike's final prediction error [13] (henceforth, FPE). The former approach gives consistently in all cases analyzed smaller values for  $n$ . It has been shown in a simulation study that SBC is the most efficient in selecting the correct model order compared to other selection methods, among which FPE [14]. Since we are interested in robust estimates, we have generally adopted the SBC.

We then perform a Monte Carlo experiment by running several times the autoregressive system having the previously obtained optimal parameters and compute the statistics of the outputs. In such simulations, the initial conditions are essentially not relevant in statistical terms. Anyway, in order to eliminate transient effects and consider statistical equilibrium conditions, granted by the stationarity of the process, we do not consider the first 1000 time steps.

This approach allows us to obtain an estimate of the standard deviation of the trend. This analysis gives in all cases a negative result, *i.e.* we obtain non-statistically-significant trends. The 95% confidence intervals consistent with the null trend hypothesis are shown in tables I and II for the amplitude and phase functions, respectively.

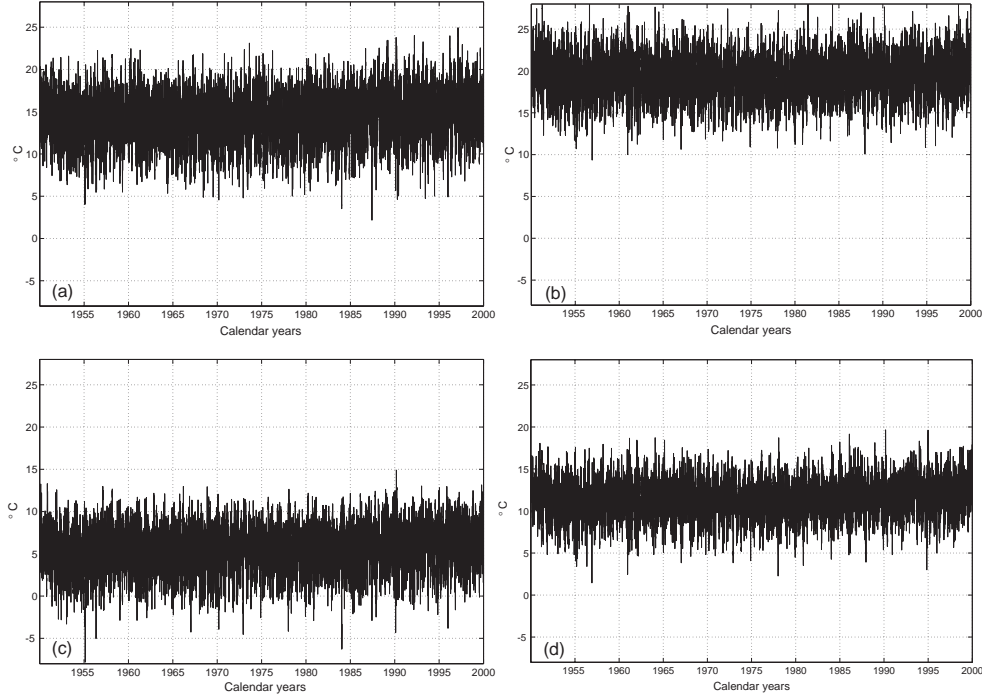


Fig. 6. – De-seasonalized maximum and minimum temperature records of station N and station S: a)  $T_{\max}^N(t) - \bar{\Sigma}(t, 2\pi/\tau_0) \{T_{\max}^N\}$ ; b)  $T_{\max}^S(t) - \bar{\Sigma}(t, 2\pi/\tau_0) \{T_{\max}^S\}$ ; c)  $T_{\min}^N(t) - \bar{\Sigma}(t, 2\pi/\tau_0) \{T_{\min}^N\}$ ; d)  $T_{\min}^S(t) - \bar{\Sigma}(t, 2\pi/\tau_0) \{T_{\min}^S\}$ .

## 6. – Notes on the de-seasonalized data

In figs. 6 we present the data sets obtained by subtracting the computed seasonal cycles to the corresponding temperature records. These data have been fitted with autoregressive models, whose order and parameters have also been estimated with suitable software [10, 11]. The main statistical properties of these data are presented in table III. In all cases the estimated optimal value of the autoregressive order, where the SBC has been adopted, is between 3 and 5, which closely resembles the characteristic time scale of the mid-latitude cyclones. The variability of the subtracted signal, which can be estimated by the value of the corresponding standard deviation, is larger for the variables referring to station N, and largest for  $T_{\max}^N$ . This might be related to the fact that mid-latitudes baroclinic weather disturbances are stronger in Northern Italy, while the Southern Italy climate is less influenced by such meteorological features. The climate of Southern Italy might depend more on the strength and position of the Hadley cell, which has a less pronounced short-time variability.

Comparing the last two columns of table III, we see that in all cases the variance of the de-seasonalized signal is smaller by about 5% than the signal obtained by erasing the  $1 \text{ y}^{-1}$  frequency component computed over all the spectrum. This implies that the local estimate of the seasonal cycle can explain a larger fraction of the total variance of the signal than the rigorously periodic seasonal signal obtained with DFT.

We underline that a correct evaluation of the seasonal signal is of outstanding im-

portance for a correct approach to the problem of determining the extremes of a given climate record. In the case of the data sets under investigation in this work, a thorough analysis of the extremes will be shortly presented in a future publication.

## 7. – Conclusions

In this work we have analyzed the data sets covering the last 50 years of daily maximum and minimum temperature which are representative of the Northern and of the Southern Italy temperature fields, respectively.

We have analyzed the seasonal cycle with the technique of cyclograms, which allows to find at each time the quasi-instantaneous best estimate of the annual component of the record. The resulting seasonal signal is not strictly periodic, since at each time the estimates of phase and amplitude change slightly.

It is important to underline that such an approach is viable because our signal obeys the narrow-band approximation, *i.e.* the spectrum of the signal has a strong, narrow peak for the annual cyclic component. If, on the contrary, the signal is characterized by a broad spectral feature comprising the  $1 \text{ y}^{-1}$  frequency component, it is a mathematical nonsense to investigate whether the seasonal cycle is changing. In such a case the seasonal cycle is just *not defined*, because several contiguous spectral components having different frequencies and shifting phase differences give contributions of comparable importance.

In all cases analyzed, the time-dependent estimates of amplitude and phase of the seasonal cycles do not show any statistically significant trend in the time frame considered. Moreover, in each case the average value of the estimates closely resembles the amplitude and phase of the 1 year frequency sinusoidal signal resulting from the Fourier analysis of the whole data set. Succinctly, *seasons seem to have not changed* in their annual evolution.

In general, the amplitude of the maximum temperature seasonal cycle is larger than that of the minimum temperature, and seasonal cycles of station N are larger than those of station S. In terms of phase, we observe that in general the minimum temperature seasonal cycle lags behind the maximum temperature seasonal cycle, and that the seasonal cycles of the station S lag behind the corresponding cycles of the station N. All seasonal cycles lag considerably behind the solar cycle.

On the one side, thermal inertia effects related to the day/night cycle explain the lag and different amplitudes of the cycles of maximum and minimum temperatures. On the other side, larger-scale thermal inertia effects related to the different thermal properties of sea and land provide a qualitative argument for the differences in amplitude and phase of the station N and S cycles. We underline that Northern Italy is more continental than Southern Italy. The data support that two effects, which we have physically referred to the the North-South and maximum-minimum (or day-night) asymmetries, sum up linearly both for phase and amplitude of the seasonal signals.

The data obtained by subtracting from the signal the corresponding seasonal cycle have been fitted as autoregressive systems, whose order and parameters have also been estimated with suitable software. In all cases the optimal value of the autoregressive order is between 3 and 5 (which is expressed in term of days) which closely resembles the characteristic time scale of the mid-latitude cyclones. The variability of the subtracted signal, which can be estimated by the value of the corresponding standard deviation, is larger for the northern variables, and largest for  $T_{\max}^N$ .

This might suggest that the climate of Northern Italy is strongly driven, in statistical sense, by the southern portions of the storm-track Atlantic eddies, while we might guess

that the northernmost branch of the Hadley cell plays a very relevant role for the climate of Southern Italy. In future work it would be possible to test such hypothesis by correlating the seasonal signal of the temperature records here analyzed with the seasonal signal of suitably defined indicators of storm-track activity and meridional circulation.

Finally, we wish to emphasize two major limitations of the present work with the perspective of providing hints for future research. We wish to underline that if on the one side the surface temperature is a very relevant quantity in terms of influence on the biosphere, including human activities, on the other side it is not the most relevant quantity in terms of representing schematically the thermodynamic properties of the system. As well known, a measure of the average tropospheric temperature is much more relevant in this sense [15]. Therefore, a more physically sensitive approach would be considering the records of the whole vertical temperature profile. Obviously, this requires the availability of long and reliable radiosonde records.

Moreover, it is important to note that, when considering a limited area, the direct solar forcing is *not* the only relevant forcing, since air advection at all levels from nearby areas plays a fundamental role in determining the state of the system under consideration. This is of special significance for areas, such the Mediterranean basin or *a fortiori* Italy, which do not have a strong *endogeneous* climate mode, as occurs in the case of the Indian Monsoon area or Siberia, and are characterized by an essentially residual climate.

Therefore, it would be important to consider in future analyses the estimates of the convergence of thermal fluxes obtained from the available reanalyses. It is important to note that especially in the case of relatively small and elongated territories such as Italy, the resolution of the data becomes of critical relevance.

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## REFERENCES

- [1] ATTOLINI M. R., CECCHINI S. and GALLI M., *Nuovo Cimento C*, **7** (1984) 245.
- [2] GALLI M., *Time series analysis with power spectrum and cyclograms*, in *Solar-Terrestrial Relationship and the Earth Environment in the Last Millennia, Proceedings of the International School of Physics "Enrico Fermi"*, edited by CINI CASTAGNOLI G., Vol. XCV (North Holland, Amsterdam) 1988, p. 246.
- [3] VINNIKOV K. Y., ROBOCK A., GRODY N. C. and BASIST A., *Geophys. Res. Lett.*, **31** (2003) L06205, DOI:10.1029/2003GL019196.
- [4] BRUNETTI M., COLACINO M., MAUGERI M. and NANNI T., *Int. J. Clim.*, **21** (2001) 299.
- [5] BRUNETTI M., MAUGERI M., NANNI T. and NAVARRA A., *Int. J. Clim.*, **22** (2002) 543.
- [6] MAUGERI M., BAGNATI Z., BRUNETTI M. and NANNI T., *Geophys. Res. Lett.*, **28** (2001) 4551.
- [7] MAUGERI M., BRUNETTI M., MONTI F. and NANNI T., *Nuovo Cimento C*, **26** (2003) 453.
- [8] ATTOLINI M. R., GALLI M. and CASTAGNOLI C. G., *Solar Phys.*, **96** (1985) 391.
- [9] ATTOLINI M. R., GALLI M., NANNI T. and POVINEC P., *Radiocarbon*, **31** (1989) 839.
- [10] NEUMAIER A. and SCHNEIDER T., *ACM Trans. Math. Softw.*, **27** (2001) 2757.
- [11] SCHNEIDER T. and NEUMAIER A., *ACM Trans. Math. Softw.*, **27** (2001) 5865.
- [12] SCHWARZ G., *Ann. Stat.*, **6** (1978) 461.
- [13] AKAIKE H., *Ann. Inst. Stat. Math.*, **23** (1971) 163.

- [14] LUETKEPOHL H., *Time J. Ser. Anal.*, **6** (1985) 35.
- [15] PEIXOTO A. and OORT B., *Physics of Climate* (American Institute of Physics, Washington) 1992.