Moving Spectral Variance and Coherence Analysis and Some Applications on Long Air Temperature Series

C.-D. SCHÖNWIESE

Institute for Meteorology and Geophysics, J.W. Goethe University, D-6000 Frankfurt 1, FRG

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ABSTRACT

Climatic records of a long time series (e.g., centuries) may be nonstationary. Thus, the stability of the variance (power) spectrum over a sequence of time periods is examined. Moreover, it is important to use different algorithms and tests in cases where there is an unknown or problematical physical background. Variance spectra of Hohenpeissenberg (FRG) annual mean air temperatures are compared using two methods, autocorrelation spectral analysis (ASA) and maximum entropy spectral analysis (MESA). These spectra are then compared with corresponding spectra based on Northern Hemisphere mean air temperature reconstructions where the ASA and MESA results are very similar. The application of a moving (running, "dynamic") variance spectrum analysis shows that, in general, the signals found in the customary "integrated" spectrum vary as time varies, namely in their occurrence, significance and "bandwidth." These findings are presented in terms of either contour lines of the relative variance (MESA) or contour lines of the confidence levels exceeded (ASA), where 50-yr subsamples are "moved" in 10-yr steps. Similarly, coherence spectra can be computed in moving terms. As an example the Northern Hemisphere data are spectrally correlated with the corresponding central England and Philadelphia air temperature series. It is shown that the coherencies are not stable in time, and that the spectral characteristics throw considerable doubt on the reliability of the reconstructed Northern Hemisphere temperature series prior to 1881. In general, moving spectral analysis of climatic time series improves the interpretation of climatic change.

1. Some remarks on "integrated" spectral variance analysis

The most common methods of time series spectral analysis are: 1) periodogram; 2) variance (power) spectrum analysis, where the Fourier transform of the autocorrelation is computed, called here ASA = autocorrelation spectral analysis; 3) fast Fourier transform, FFT; 4) maximum entropy spectral analysis, MESA (or maximum entropy method, MEM). For details see, e.g., Båth (1974), Blackman and Tukey (1958), Essenwanger (1951), Mitchell et al. (1966), Panofsky and Brier (1958), Radoski et al. (1975), Schönwiese (1985) and Essenwanger (1986).

There are some advantages of the ASA method, particularly the availability of comparably simple significance tests. These tests are usually based on a first-order autoregressive (AR1) Markov process and, in consequence, a red noise null hypothesis, where the χ^2 distribution is used for determining the confidence limits for the sample spectrum peaks. (For definitions and problems see, e.g., Essenwanger, 1980, and Mitchell et al., 1966.) Although red noise (or white noise, if the lag 1 autocorrelation coefficient is not statistically significant) is assumed to define the autoregressive structure of the population from which the sample is drawn, a higher order AR process would sometimes be a more appropriate null hypothesis.

The outstanding advantage of the MESA method (periodogram and FFT are not appropriate in this context) is the increased spectral resolution in the low-frequency domain (relatively long periods). When, however, the algorithm parameters (ASA: number of lags; MESA: number of coefficients) are varied it can be empirically verified that the MESA based variance values vary much more than the corresponding ASA values. This means that the amount of variance estimated by the MESA method (for example, algorithm after Burg, 1972) at any particular frequency band may not be stable, whereas the frequencies themselves, however, are comparatively stable. This complicates the significance tests. Following Livezey and Chen (1983), in addition, Monte Carlo techniques should be used in order to supplement the test algorithms and to avoid misinterpretations due to interdependence effects (of data and tests).

Nevertheless, one should be aware of the fact that every sample variance spectrum may contain peculiar statistical artifacts and, in general, it is not possible to discern these artifacts from real physical effects, particularly if these physical effects are not known or are problematic. Different algorithms, however, reveal different artifacts (again in general). Therefore, this is a further argument for analyzing any given database by means of at least two different and largely independent algorithms. Then, differences in the results may well

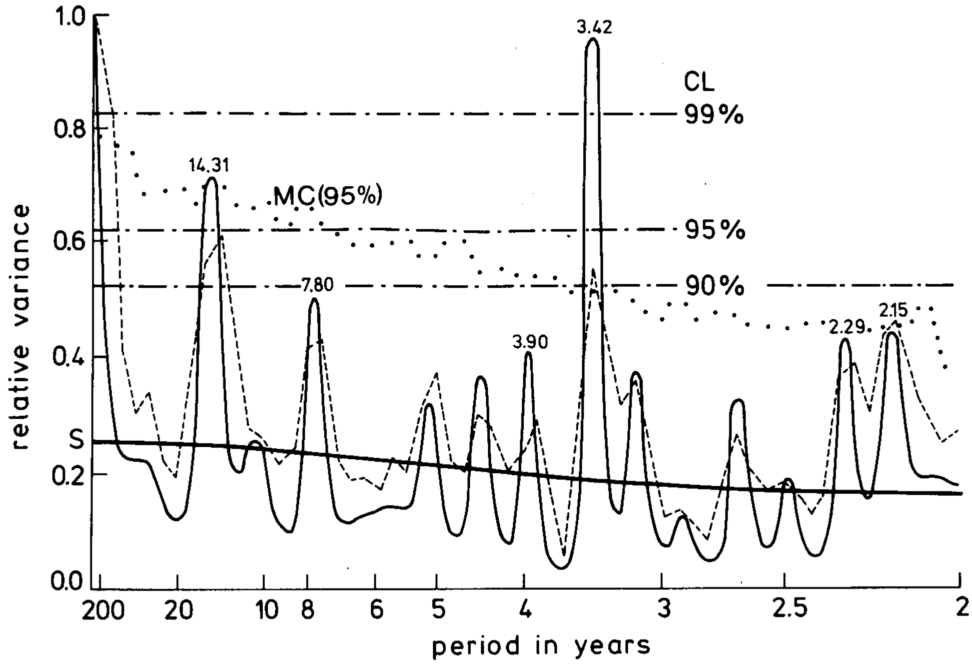

FIG. 1. Maximum entropy spectrum (MESA) of the Hohenpeissenberg (FRG) annual mean temperatures, 1781–1980 (Burg algorithm, 60 coefficients, 642 frequencies; smoothed spectrum S: two coefficients). For comparison variance spectrum (ASA, dashed line, 100 lags), same time series, including confidence levels (χ^2 test) CL 90%–99% (or error probabilities 0.1–0.01). The variance is normalized, where the maximum (1.0) of relative variance corresponds to 5.5% of the total variance (ASA). The dotted line represents a MESA 95% confidence estimation based on 500 random time series (Monte Carlo technique MC).

be due to artifacts, and similarities may be (but not necessarily) reliable. In comparing ASA and MESA, neither can be claimed to be the "better" technique. One can only try to combine advantages and to eliminate disadvantages.

In Fig. 1, the ASA (dashed line) and MESA spectra of the Hohenpeissenberg (mountain station in southern Germany near the Alps) mean annual temperature from 1781 (start of observations) to 1980 are plotted. The observations are, to a relatively high degree, reliable and homogeneous (Schönwiese and Malcher, 1985). Note the similarities in the sample spectrum peaks (signals), although only the ca 3.4- and ca 14-yr cycles (mean periods) exceed the 90% confidence level (or 0.1 error probability), which means relatively weak significance, and only the long-term residuum exceeds the 99% level. The Monte Carlo simulations for the MESA sample spectrum confidence levels reveal similar results where the 3.4- and 14.3-yr peaks and the long-term residuum exceed the 95% confidence level. This is shown in Fig. 1 by means of a dotted line. (Details and results of a worldwide spectral analysis of 242 temperature and 164 precipitation time series are given in Schönwiese et al., 1986.)

This spectrum is compared (see Fig. 2) with a corresponding MESA spectrum of the reconstructed Northern Hemisphere mean annual temperatures 1781–1980. [Note that continental areas are emphasized; data before 1881 are from Groveman and Landsberg (1979); later, data are from Borzenkova et al. (1976); updatings are from Jones et al. (1982).] Here, ca 2.6- and 5.4-yr cycles become more prominent and instead of a ca 14-yr cycle, a ca 12-yr cycle is indicated. The latter is, however, not correlated with the sunspot variations (see Schönwiese, 1983, 1984). In these papers a more detailed analysis of this record is discussed, where the quasi-biennial oscillation (QBO) exceeds the 99% confidence level over both the 1881–1980 (mean period 2.05 yr) and 1579–1980 interval (mean period 2.13 yr). It should be remembered, however, that the Northern Hemisphere data reconstructions before 1881 and particularly before 1781 are very uncertain, because of both the proxy database (tree ring series) and possible regression instabilities (including coherence problems; see Jones and Kelly, 1983).

There arise three questions: 1) Are these signals really significant and stable in time? 2) Are these signals of a global (hemispheric) or a more regional (local) type? and 3) What are the physical reasons for these signals?

No doubt, the last question is the most difficult one. There are a lot of suggestions concerning the QBO. Relatively long-term variations may be due to external forcing of the climate system like volcanism (also affecting the year-to-year variations) and solar irradiation change (see, e.g., Gilliland, 1982; Hansen et al., 1981; Schönwiese, 1984; Schuurmans, 1981). We are, however, far from understanding a lot of other spectral signals which may or may not be statistically significant.

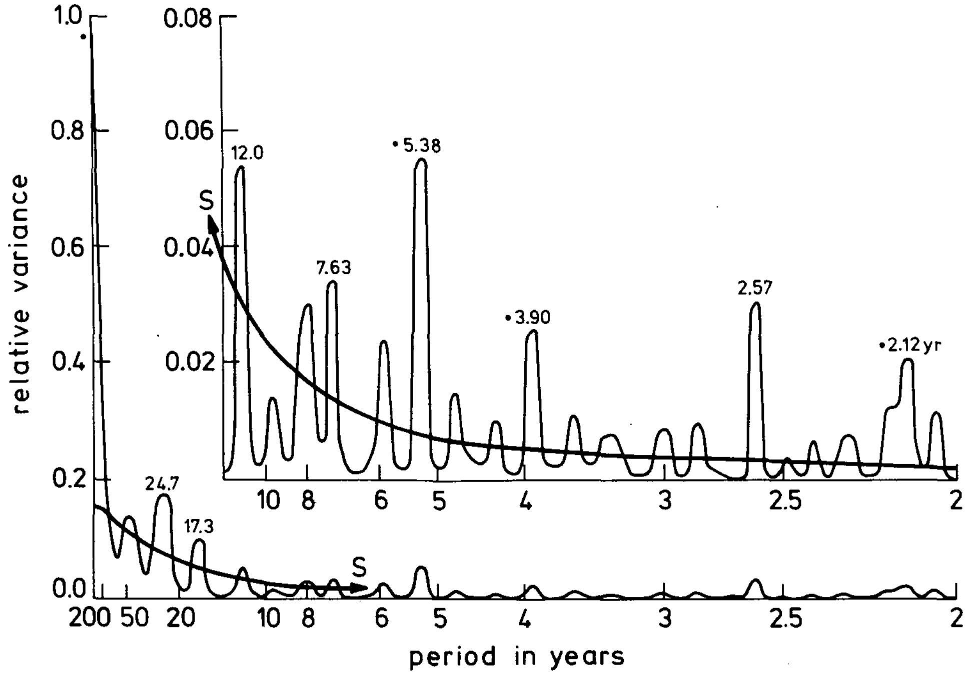

FIG. 2. Maximum entropy spectrum (MESA, 60 coefficients, 657 frequencies) of the Northern Hemisphere (average) mean annual temperatures. Normalization of variance (1.0 corresponds to 25.5% of total variance) and smoothed spectrum S as in Fig. 1. Dots before the numbers of predominant periods mean that these peaks exceed the 95% confidence level in respect to both conventional (χ^2) and Monte Carlo tests.

Many of them—for instance, the quasi-5-yr cycle (Fleer, 1981) and probably also the ca 3-4- and ca 8-yr cycles may be produced by atmospheric–oceanic circulation mechanisms such as the Southern Oscillation/El Niño phenomenon. Most hypotheses, however, are speculative.

Nevertheless, it is still reasonable to proceed in answering the first two questions which may, in turn, enable us to make progress in the understanding of the physical background. The first question can be discussed by means of moving spectral analysis, whereas the second should be followed by analyzing the regional and local spectral variability and its spatial coherence.

2. Moving spectral variance analysis

In general, all climatic time series statistics vary as time varies. This gives rise to ambivalent consequences. On the one hand, the estimation of the confidence levels of the spectra becomes problematic because time-dependent autocorrelation variations cause time-dependent red noise variations on which these estimations are based. On the other hand, the signals detected in the customary "integrated" spectrum (Figs. 1 and 2) can be studied in a "dynamic" way by considering their variations in time.

An adequate tool to do this is moving (running, "dynamic") spectral analysis; for some early work on this subject see Olberg and Schönermark (1981) and Junk (1983). Figures 3 and 4 present two examples of such an analysis. The Hohenpeissenberg temperature series 1781–1980 is subdivided in 50-yr subintervals and spectral analysis is performed by moving the subintervals in steps of 10 years (1781–1830, 1791–1840, etc.) using both the ASA and MESA method. The outcome is plotted in terms of contour lines of relative variance (in the MESA case, see Fig. 3), or in terms of contour lines of the confidence levels exceeded (in the ASA case, see Fig. 4). Obviously the overlapping time series spectra (for each subinterval) are not independent from each other which implies some "smoothing" of the overall moving spectrum.

In detail, Fig. 3 reveals the following: the QBO, very weak in the "integrated" spectrum (Fig. 1), is outstanding here but vanishes roughly after the 1851–1900 subinterval. Also, a distinct quasi-5-yr cycle is detectable, restricted, however, to a comparably short time interval. The 3–4-yr cycle, outstanding in the "integrated" spectrum, loses a good deal of its dominance and the 14-yr cycle is indicated only near the beginning and the end of the record. Longer cycles cannot be identified due to the smaller time subintervals. (For a similar moving analysis of the Northern Hemisphere data see Schönwiese, 1984.) Note that this moving way of spectral analysis enables also a characterization of the "bandwidth" variations of the signals, i.e., of the frequency interval which is covered by any particular variance component. (In order to study these signals

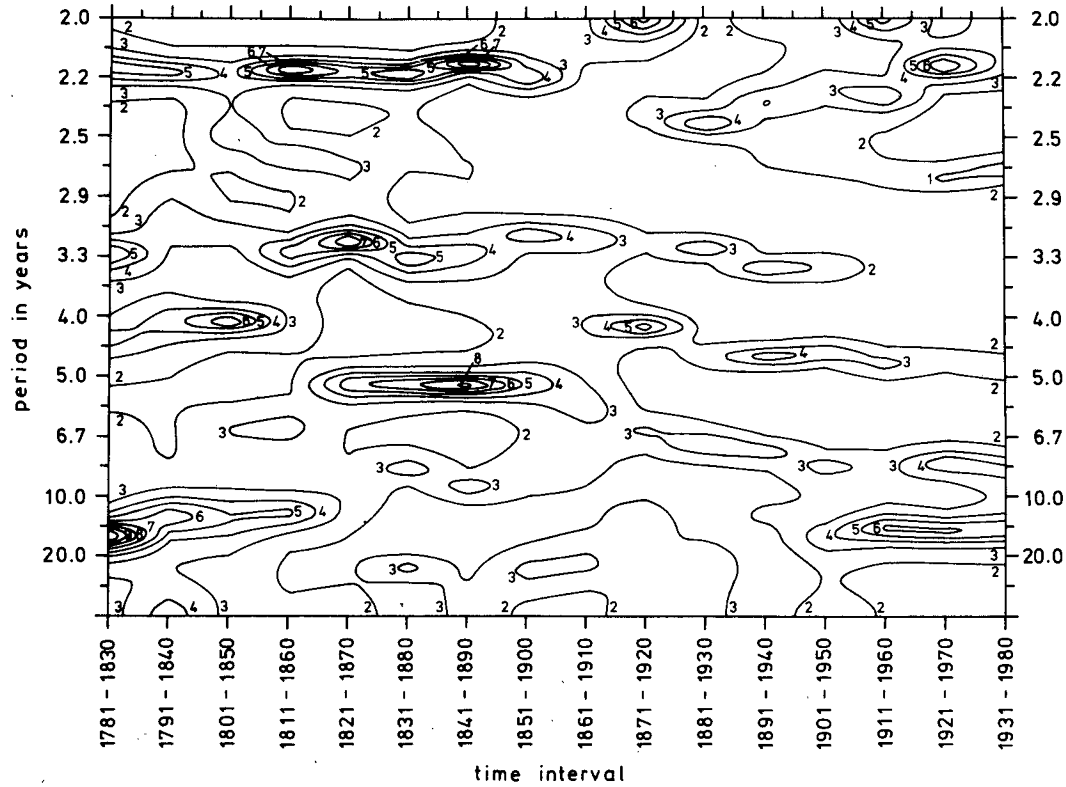

FIG. 3. Moving maximum entropy spectrum (MESA) of the Hohenpeissenberg annual mean temperatures, 1781–1980, in 50-yr subintervals and overlapping 10-yr steps (each subinterval spectrum 15 coefficients). The numbers denote "contour lines" of the relative variance in tenths, normalization as in Fig. 1. Ordinate scale in years (period).

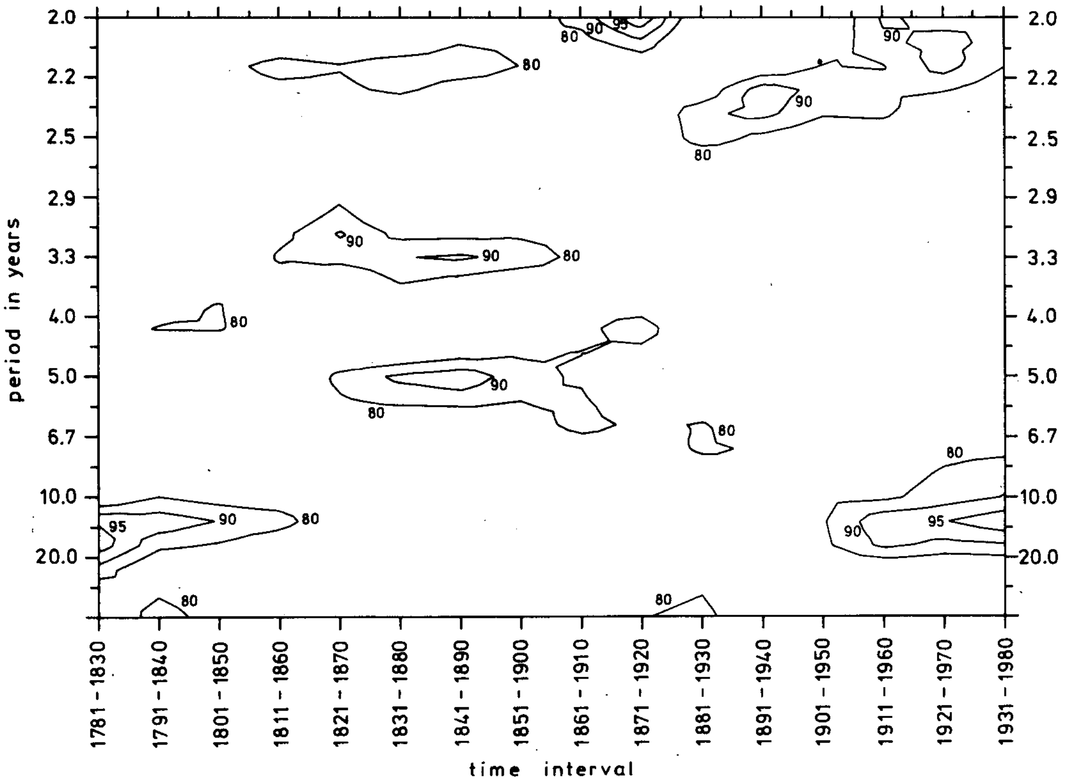

FIG. 4. Moving variance spectrum (ASA) with same time series and subintervals as in Fig. 2 except "contour lines" indicate confidence levels (in percent) exceeded (each subinterval spectrum 25 lags).

in the time domain, an additional technique is needed—of course, band-pass filtering.)

Similar but not identical results arise from another point of view, the moving analysis of the ASA based confidence levels presented in Fig. 4. Only a few results are mentioned here. The QBO related confidence level is higher in the later time subinterval (note the contrast to Fig. 3). In this later subinterval, moreover, a change of the cycle length is indicated; compare the two MESA peaks 2.29 and 2.15 yr in Fig. 1 which can be now attributed to one mechanism changing its cycle length. The time-dependent characteristics of the ca 3.4- and ca 5-yr cycles are very similar in both the moving MESA and ASA results. (In Fig. 3 the ca 5-yr cycle is more prominent.) Finally, the highest confidence levels are those associated with the ca 14-yr cycle at the beginning and the end of the record and a ca 2.0-yr cycle existing around 1871–1920.

Considering these results—specifically, the differences between the ASA and MESA results, the often weak significance and the transience of many of the spectral peaks—the outcome of the algorithms and the tests applied seems to be no better than one would expect by chance. Are we describing sample spectra drawn from a random process? This can be actually neither confirmed nor refuted. The following, however, should be realized. 1) Applying the ASA algorithm used here to random numbers (same sample size, $M = 100$ lags) it is found that, on average, no peak exceeds the 99% and one to two peaks exceed the 95% confidence level. Similar results can be revealed using Monte Carlo techniques concerning the MESA results. The climatic data results seem to be somewhat more confident (but not convincingly). 2) The QBO reflected in the climatic data spectra is probably due to a real physical process so that it cannot be strictly concluded that this and other sample spectrum peaks of similar magnitude are simply artifacts of the algorithms. 3) A great number of temperature spectra from all over the world indicate again and again a few predominant frequency bands of the variance observed, in contrast to a random process (Schönwiese et al., 1986). 4) There are signs of statistically significant nonstationary climatic data records, also in contrast to a random process. (Note that also a number of physical processes like volcanism, El Niño or QBO are nonstationary.)

3. Moving coherence analysis

Concerning question 2 in section 1, one has to ask whether the signals detected in the "integrated" and moving variance spectra are of global (hemispheric) or more regional (local) character. One way to do this is to collect variance spectra of regional or local time series data—as much as possible—and to look for similarities; similarly, mean regional spectra can be computed (see, e.g., Fleer, 1981; Schönwiese, 1978; Schönwiese et al., 1986). In addition, the (cross-spectral) coherence can be analyzed between stations, regions, or between the Northern Hemisphere and these stations or regions.

Figure 5 characterizes the spectral variance of two additional air temperature time series: central England (regional, data after Manley, 1974, updated) and Philadelphia (local). Evidently these two spectra (MESA)

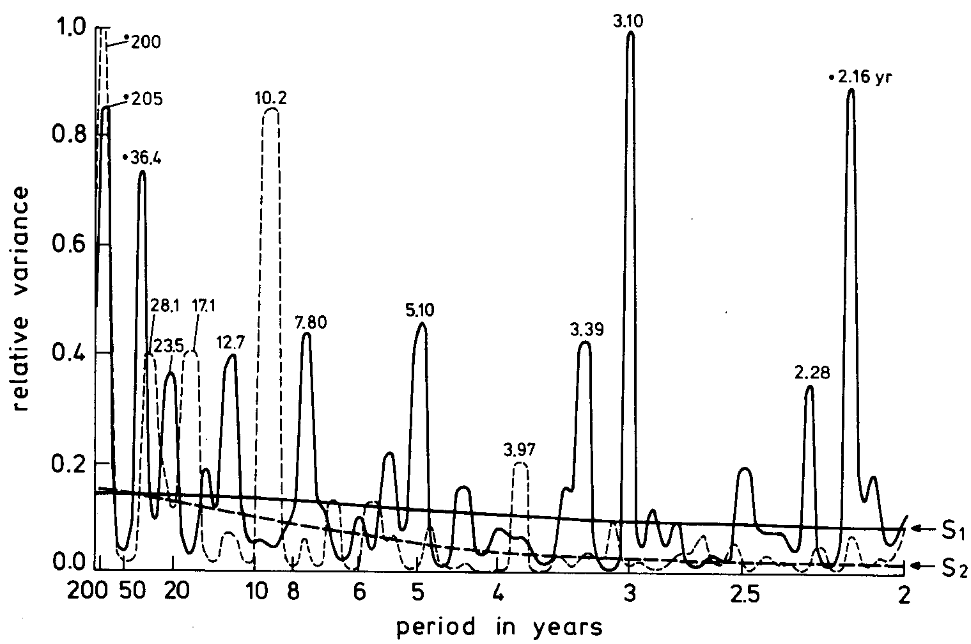

FIG. 5. Maximum entropy spectra (MESA) of central England (solid line) and Philadelphia (dashed line) annual mean temperatures, 1781–1980 (60 coefficients, 618 and 643 frequencies, respectively). Normalization as in Fig. 1 (1.0 corresponding to 5%, central England, or 10%, Philadelphia, of the total variance). Note that S_1 and S_2 are the corresponding smoothed spectra (two coefficients), dots as in Fig. 2.

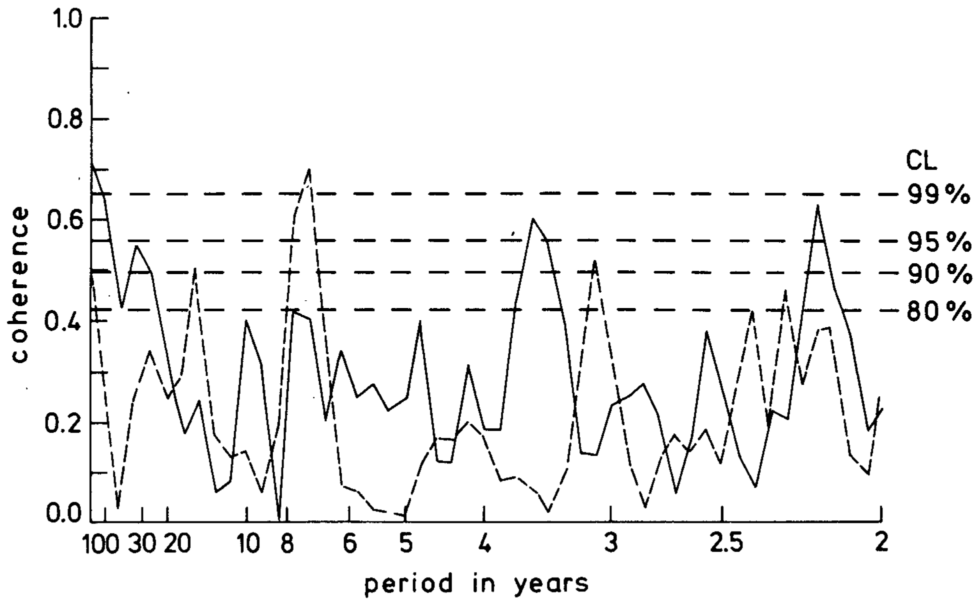

FIG. 6. Squared coherence of annual mean temperatures, 1781–1980, where the Northern Hemisphere data are correlated with those of central England (solid line) and Philadelphia (dashed line) (ASA, 50 lags, including confidence levels CL).

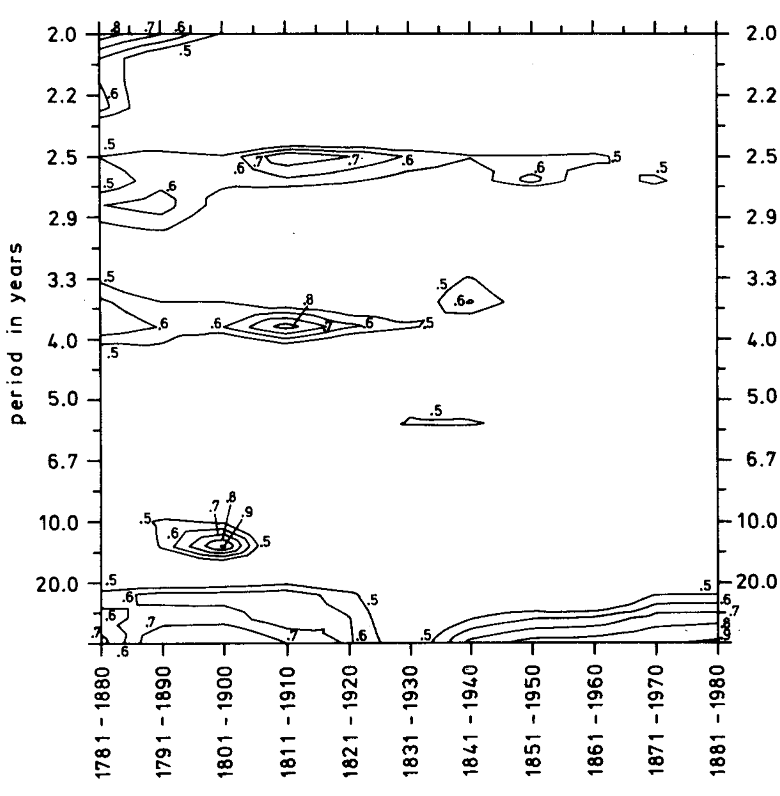

FIG. 7. Moving squared coherence of annual mean temperatures, 1781–1980, in 100-yr subintervals and overlapping 10-yr steps (ASA, each subinterval spectrum 25 lags), where the Northern Hemisphere data are correlated with those of central England. The numbers denote squared correlation coefficients (<0.5 omitted). Ordinate scale in years (period).

are very different from each other and also from the Hohenpeissenberg spectrum (Fig. 1). Note, for instance, the outstanding QBO signal in the central England series, in contrast to Hohenpeissenberg. [The 3.1-yr peak, a little bit higher in the central England "integrated" spectrum, is relatively unstable in time when compared with the 2.16-yr peak and seems to cover shorter time subintervals in the moving spectrum (Schönwiese et al., 1986).]

In Fig. 6 the (squared) coherence spectra (this means spectral analysis of the squared correlation coefficient) of these two time series with the Northern Hemisphere data are presented. The results are as follows. The long-term residuum is coherent for central England (99% confidence level exceeded), but this coherence is considerably less well established for Philadelphia. Furthermore, a ca 8-yr signal is coherent in the case of Philadelphia, whereas in the case of central England, signals of ca 3.8- and ca 2.2-yr (QBO) are coherent with the Northern Hemisphere data. There is, of course, some "automatic" correlation because the Northern Hemisphere reconstructions are based, besides others, also on these time series. The matter of interest, however, is the evaluation of typical (more or less significant) differences of the cross-spectrum statistics.

Coherence analysis can also be studied in a time-dependent way. Figures 7 and 8 display the moving coherence over the period 1781–1980 between the Northern Hemisphere temperature and the corresponding records of central England or Philadelphia, where the subinterval length is 100 yr. Again, there are variations in time. The long-term variance component shows greater coherence (except some earlier subintervals) after the 1831–1930 subinterval (central England a little bit later). For approximately the first half of the time series a ca 12-yr signal is coherent between Philadelphia and the Northern Hemisphere data. For central England, this signal exceeds the 95% confidence level only in the 1801–1900 subinterval. A coherency within the ca 3.5–4.0 yr band is found only in case of central England. The QBO coherencies (roughly 2.2–2.5 yr, also 2.0 yr for central England in the first two subintervals) are detectable in both time series. [Note that a coherence value of 0.6 corresponds approximately to a confidence level of 95% for sample size 100 yr and $M = 25$ lags; see the so-called Goodman formula (Panofsky and Brier, 1958; Mitchell et al., 1966).]

There is an interesting aspect which can be concluded from these analyses with regard to the Northern Hemisphere temperature reconstructions by Groveman and Landsberg (1979) which are based on a regression analysis calibrated over the period 1881–1975. For central England, the 1881–1980 coherence of the Northern Hemisphere temperatures is established predominantly in the low-frequency domain. (For Philadelphia, the 1881–1980 coherence is also existent in the ca 5–8 yr band.) Prior to 1881, however,

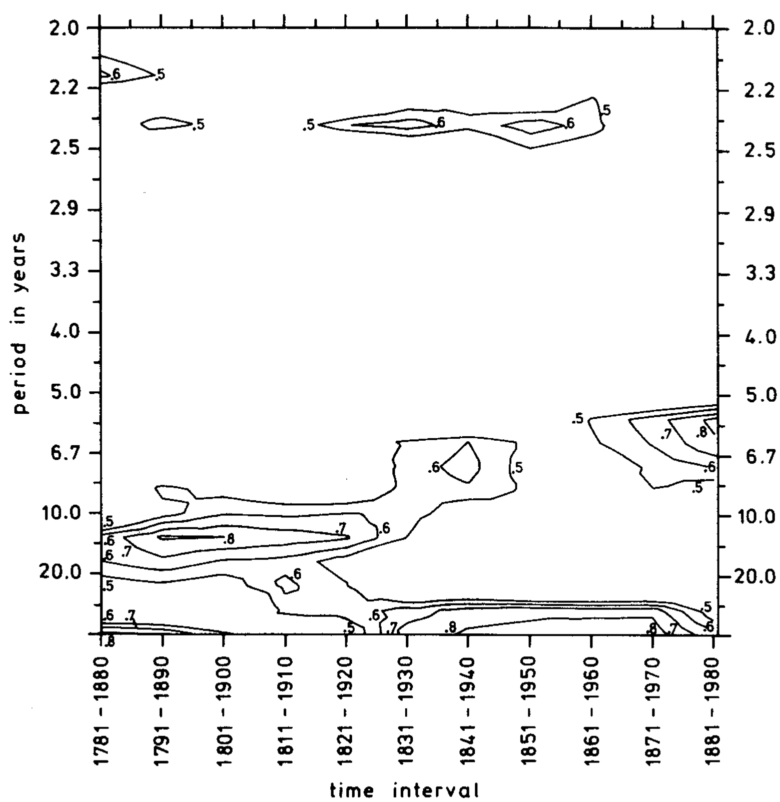

FIG. 8. As in Fig. 7, but for Philadelphia instead of central England.

the Northern Hemisphere series shows entirely different coherencies with central England and Philadelphia; this is just the reconstruction period of the Northern Hemisphere data. Moreover, the coherencies are not stable in time, in particular before the ca 1831–1930 (or 1841–1940) interval. Hence, the spectral characteristics fail to verify the calibration and the Northern Hemisphere reconstructions before 1881 must be considered suspect. This conclusion is supported by the work of Jones and Kelly (1983) who showed that correlations between local and Northern Hemisphere temperature time series are generally unstable in time.

4. Some conclusions

These very fragmentary and preliminary results illustrate that a moving view of the spectral statistics of time series provide more insight into the character of climatic change than the conventional "integrated" method. In cases where there is an unknown physical background, it is important to use different and largely noninterdependent algorithms and confidence tests. These different methods, including moving spectral techniques, may be helpful in identifying (or searching for) physical processes, particularly those which are not stable in time.

Even when the sample spectra describe random processes, moving spectral statistics may be of interest because it is possible that these processes produce different spectral modes of climatic change which are also not stable in time. [Compare "synergetic" random theory, in particular "bifurcations" (Haken, 1983).]

It is often stated that climatic change cannot be explained by statistics. This is true. It is not possible, however, to understand the enormously complicated climate system, which has so many degrees of freedom, by applying only a few strategies or by restricting oneself to deterministic modeling (which needs verification by observational statistics). Like a detective, one has to collect and to interpret a large number of clues. Statistical analysis can help to identify and clarify these clues. As many reasonable views as possible must be used in order to throw light on the climate system. The "detection" of causes will not be one of the first, but one of the last steps of these investigations.

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