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Statistical predictability and spectra of air temperature over the northern hemisphere

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ABSTRACT

Parametric models and statistical predictability of mean annual air temperature, both at individual stations (MAAT) and zonally averaged (MZAT), are evaluated. The time series have lengths from 125 to 315 years for MAAT and 86 years (1891–1976) for MZAT. The optimal parametric models of MAAT are shown to be closely approximated by a first-order Markov sequence with a small characteristic time scale, so that their statistical predictability is minimal. Variations in MZAT should be described with more complicated models; the limits of statistical predictability amount to between 4 and 5 years. The temperature spectra are estimated, and the relatively high statistical predictability is shown to result from the concentration of spectral energy at low frequencies.

1. Introduction

The study of the statistical properties of the observed climate is nowadays regarded as a major problem in physical climatology (GARP, 1975, 1977). In this respect, year-to-year variations of geophysical processes with time scales from several years to several decades ("climatic variability", according to Gruza and Rankova, 1980) are of substantial theoretical and practical importance, because these processes determine e.g., the natural climatic variations during the span of human life, or the service time of technological projects. Experimental studies of processes with such time scales are also necessary in order to develop adequate physical climate models.

In this paper, an attempt is made to assess statistical properties of mean annual air temperature (MAAT) over the northern hemisphere using both observations at individual stations and time series of zonally averaged temperature. Statistical predictability is characterized here by the quality of least-squares linear predictions of temperature by its present and past values.

It should be noted that studies of statistical predictability of climatic processes with time scales from several years to several decades are by no means numerous (Privalsky, 1976, 1977a, b). Spectra of large-scale processes have been analysed by several groups (see e.g., Monin and Vulis, 1971; Poljak, 1975, 1979) using traditional non-parametric spectral estimates. Parametric methods have been used by Petersen and Larsen (1978) to analyse and forecast long-term climate variations.

2. The data and methods

Variations of MAAT at *individual stations* (in Europe and Saint-Louis, USA) are represented in 20 time series whose length varies from 125 to 315 years (Table 1). The data are taken from several sources (mostly from World Weather Records) and seem to be sufficiently reliable. A detailed description of most of these time series is given in Poljak (1975) where it is shown in particular, that none of them contain a statistically significant linear trend.

Variations of *mean zonal air temperature* (MZAT) are represented here in 16 time series of mean annual air temperature during 1891–1976 ($n = 86$). The values of surface air temperature were taken from monthly synoptic charts, interpolated to grid-points of a grid with 5° latitudinal by 10° longitudinal steps and then averaged inside their respective latitudinal zones (Gruza and Rankova, 1980). The resulting MZAT time series

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were checked for homogeneity with respect to their mean values; comparison with other similar data revealed no significant systematic errors or discontinuities (Vinnikov et al., 1980). However, the number of stations which have been used to obtain these data has increased from several hundred during the first half of the time interval to about a thousand at the present time. This means that the results obtained on the basis of these time series should be considered with caution, especially for the polar and equatorial regions (90, 85, and 15° N). Still, this data set as a whole is thought to be sufficiently reliable for an analysis of the statistical properties of MZAT. A more detailed description of the data handling procedure and their quality is given in Poljak (1979), Gruza and Rankova (1980) and Vinnikov et al. (1980). All air temperature time series were checked for stationarity. An example is given in Fig. 1. The analysis includes the selection of an optimal parametric model ARMA (p, q) within the family of mixed autoregressive-moving average models of order (p,q), the estimation of the spectral density $s_{p,q}(f)$ corresponding to the chosen model and the variance $D_{p,q}(\tau)$ of the least-squares linear prediction errors at lead times τ.

The necessity of the parametric approach is dictated in this case by the short lengths of the time series as well as by the convenience of the solution of the prediction problem.

Statistical predictability of air temperature is characterized here by two criteria. The first one is the relative prediction error (RPE) at unit (i.e., 1 year) lead time,

$$d_{p,q}(1) = D_{p,q}(1)/\sigma_T^2 \tag{1}$$

where $\sigma_T^2 = D_{p,q}(\infty)$ is the variance of temperature variations for a given time series. The second criterion—the limit of statistical predictability (LISP) $\tau_{p,q}$ corresponding to the model chosen for a given series—is defined here as the lead time τ at which the relative error $d_{p,q}(\tau) = D_{p,q}(\tau)/\sigma_T^2$ reaches the 80% level. Note that the correlation coefficient $\rho(\tau)$ between the actual temperature $T_{t+\tau}$ and its predicted value $\hat{T}_t(\tau)$ at lead time τ is $\rho(\tau) = [1 - d_{p,q}(\tau)]^{1/2}$, which means that when the limit of predictability $\tau_{p,q}$ is reached, the coefficient $\rho(\tau_{p,q}) \sim 0.45$.

Parameters of mixed autoregressive-moving average models ARMA(p,q) and autoregressive models AR(p) were estimated for each time series of MZAT by using the approximate maximum likelihood method with subsequent diagnostic checking (Box and Jenkins, 1976); a simpler method of Burg (see Smylie et al., 1973) has also been used for autoregressive models. This technique has been mostly applied to estimate models of MAAT at individual stations.

An initial estimate of the optimal order (p,q) for each time series is found on the basis of the Akaike criterion (Akaike, 1976)

$$\mathrm{AIC}(p, q) = n \ln[(n - p - q)\, D_{p,q}(1)] + 2(p + q) \tag{2}$$

and—for autoregressive models only—the Parzen criterion (Parzen, 1977)

$$\mathrm{CAT}(p) = \frac{1}{n} \sum_{j=1}^{p} D_{j,0}^{-1} - D_{p,0}^{-1}(1) \tag{3}$$

The best model is the one for which the value of the criterion is smallest.

Note also that the spectral estimate $s_{p,0}(f)$ that corresponds to the autoregressive model AR(p) of optimal order p is a maximum entropy estimate with n/p degrees of freedom (Ulrich and Bishop, 1975).

The problem of making the best choice from the

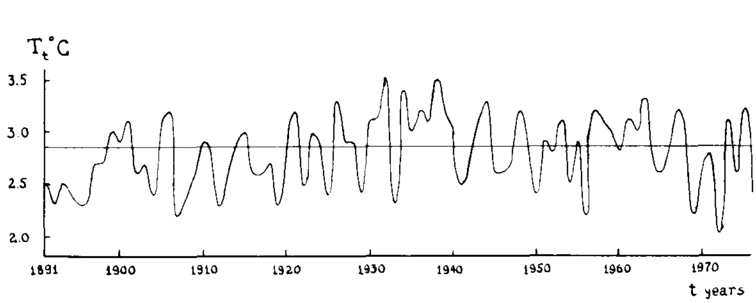

Fig. 1. Variation of mean zonal air temperature at 55° N.

family of mixed ARMA(p,q) models requires some comment. First, for the time series of MAAT at individual stations, the choice can be limited by autoregressive models only. This happens because these time series, being virtually unpredictable from their present and past values, are rather similar to white noise (though their spectra may change substantially with frequency) and therefore, when an autoregressive model is being changed to an appropriate ARMA(p,q) approximation, no appreciable change in the temperature predictability is observed. The time series of MZAT as a rule differ markedly from the white noise model, and estimates of their spectra may contain statistically significant maxima.

Both criteria, AIC$(p,0)$ and CAT(p) always led to the same order of autoregressive models, but, as for mixed ARMA(p,q) models, it seems that the choice of the order (p,q) can hardly be made, using only the Akaike criterion AIC(p,q). In 7 instances, the value of AIC(p,q) has been minimal for a mixed model, but 5 of these proved to be unacceptable either because the estimates of their parameters were correlated too closely (correlation coefficients up to 0.95) or because the roots of the characteristic equation corresponding to the model were dangerously close to the unit circle. It seems that the final selection of the best model cannot be made without the diagnostic checking of models as recommended by Box and Jenkins (1976). At least, this seems to be true when the length of the time series is small, as it is in this case.

3. Results

Variations of MAAT at different stations in Europe and in Saint Louis, U.S.A, possess very low statistical predictability. In most cases, RPE exceeds the 90% level even at the unit lead time so that the limit of statistical predictability, as it is defined here, amounts to less than 1 year (see Table 1). A typical spectrum of MAAT follows a "red noise" model with the energy decreasing rather slowly with increasing frequency. At some stations (Leningrad, Kazan, Stuttgart, Jena) the spectra contain 1 or even 2 (Archangel) peaks but, as a rule, the peaks are statistically insignificant (Fig. 2).

Table 1. *Parameters of stochastic models of air temperature at individual stations*

No.	Station	Period (years)	n	Mean value ($\bar{T}$ °C)	σ_T °C	p ($q = 0$)	$d_{p,q}(1)$ (%)	$d_{1,0}(1)$ (%)
1	Leningrad	1805–1975	171	4.0	1.26	5	92	95
2	Kazan	1828–1975	148	3.3	1.00	4	92	96
3	Archangel	1834–1975	142	0.6	1.27	5	95	99
4	Strasbourg	1806–1905	150	10.0	0.73	1	99	99
5	Prague	1775–1955	181	9.3	0.88	2	96	96
6	De Bilt	1755–1955	201	9.1	0.71	0	100	99
7	Saint-Bernard	1818–1955	138	−1.6	0.66	2	96	98
8	Berlin	1756–1955	200	9.2	0.84	2	98	99
9	Trieste	1803–1955	153	14.2	0.61	0	100	100
10	Hohenpeissenberg	1781–1955	175	6.2	0.78	2	98	99
11	Basel	1755–1957	203	9.0	0.71	3	93	97
12	Jena	1821–1955	135	8.5	0.82	6	95	100
13	Wien	1775–1955	181	9.3	0.82	0	100	100
14	Zwannenburg	1735–1940	206	9.0	0.73	0	100	100
15	Stuttgart	1792–1955	164	10.0	0.83	4	86	93
16	Karlsruhe	1799–1955	157	9.3	0.76	3	88	94
17	Paris	1757–1953	197	10.9	0.73	2	91	96
18	Budapest	1780–1960	181	10.9	0.77	1	99	99
19	Central England (52°30′N–53°N, 1°45′W–2°15′W)	1659–1973	315	9.1	0.60	4	88	94
20	Saint Louis	1836–1960	125	13.3	0.83	3	92	94

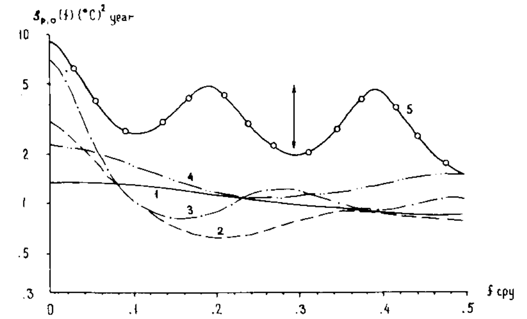

Fig. 2. Spectra of mean annual air temperature at individual stations (maximum entropy estimates): 1—Strasbourg; 2—Basel; 3—Stuttgart; 4—Berlin; 5—Archangel. The arrow shows the 90% confidence interval for the spectral estimate of MAAT at Archangel.

The exceptions are given by the spectral estimates of MAAT at Jena and Archangel (curve 5 at Fig. 2) which reveal maxima at $f = 0.17$ cpy and $f = 0.39$ cpy respectively, statistically significant at confidence level 0.9.

Statistical properties of *mean zonal air temperature* (Table 2) are notably different from those of air temperature at individual stations. At latitudes between 25° N and 80° N, the best parametric models for the temperature time series have orders from 2 to 6, with zeroth order of the moving average operator for all latitudes except for 80° N and 75° N. At higher latitudes, the order is increased to 7, while at lower latitudes it drops to 1, but no regularity is seen in the change of the models order with latitude.

Spectral estimates of MZAT (Fig. 3) sometimes contain 1 or 2 peaks inside the frequency band between 0.2 and 0.4 cpy, but as a rule, the peaks are statistically insignificant. The peaks are especially strong in the temperature spectra in the polar region where the time series are probably least reliable. The most characteristic feature of the spectra is the concentration of energy inside the low-frequency range, up to approximately 0.1 cpy. The percentage of energy $v_{p,q}(0.1)$ contributed by the frequency range from 0.0 to 0.1 cpy, that is

$$v_{p,q}(0.1) = \sigma_T^{-2} \int_0^{0.1} s_{p,q}(f)\, df \quad (4)$$

amounts, as a rule, to more than half of the overall energy (see Table 2 and Fig. 4). Near the equator and at temperate latitudes, the energy contributed by the low-frequency range drops to 40% and less.

The one-step (i.e., 1 year) least-squares linear prediction rms error is largest (about 0.7 °C) at

Table 2. *Parameters of stochastic models of mean zonal air temperature*

°N	T°C	σ_1 °C	p,q	$d_{p,q}(1)$ (%)	$d_{1,0}(1)$ (%)	$\tau_{p,q}$ (years)	$\tau_{1,0}$ (years)	$v_{p,q}(0.1)$ (%)	$v_{1,0}(0.1)$ (%)
90	−19.4	0.92	7,0	66	80	4	1	62	45
85	−18.3	0.89	7,0	64	78	4	1	63	47
80	−15.7	0.85	1,1	60	68	4	1	71	55
75	−12.4	0.73	1,1	56	63	5	2	74	59
70	−9.2	0.61	3,0	60	70	4	1	70	54
65	−5.0	0.52	6,0	69	83	6	1	65	42
60	−0.6	0.41	5,0	80	92	1	<1	50	34
55	2.8	0.35	4,0	90	99	<1	<1	30	25
50	5.8	0.30	5,0	89	99	<1	<1	34	25
45	10.1	0.26	6,0	81	89	1	<1	53	37
40	15.0	0.22	3,0	66	73	3	1	66	52
35	18.9	0.21	3,0	58	65	4	2	71	59
30	22.0	0.19	4,0	60	67	4	1	69	56
25	24.2	0.18	3,0	70	72	1	1	53	52
20	26.0	0.21	1,0	81	81	1	1	44	44
15	27.1	0.25	1,0	85	85	<1	<1	40	40
15–90	12.5	0.21	4,0	53	58	5	2	75	64
20–80	11.4	0.31	4,0	53	61	5	2	75	62
35–80	5.0	0.28	4,0	54	66	6	2	76	58
50–65	1.3	0.34	5,0	78	93	2	1	52	32
15–50	19.5	0.16	1,0	67	67	1	1	57	57

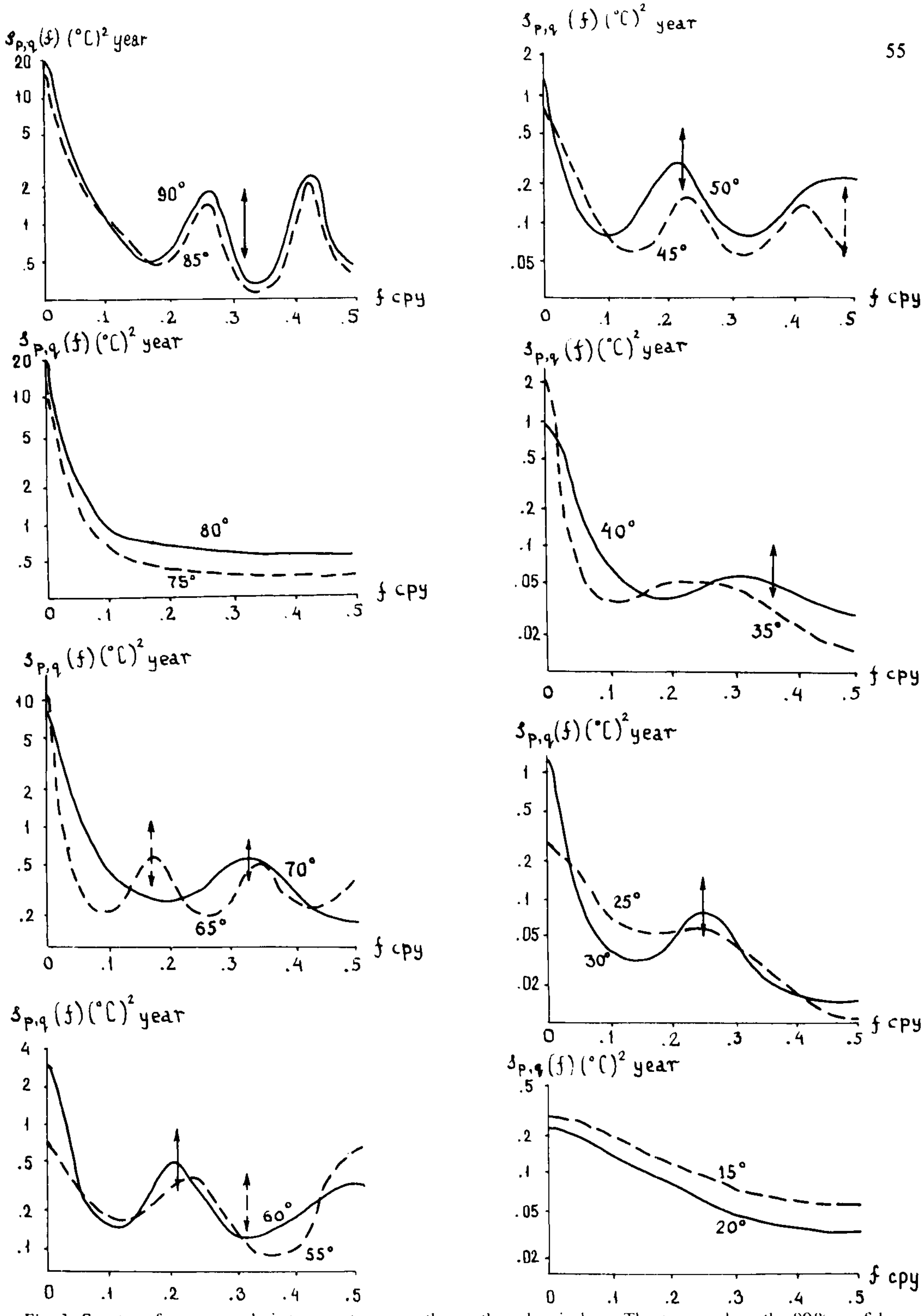

Fig. 3. Spectra of mean zonal air temperature over the northern hemisphere. The arrows show the 90% confidence intervals.

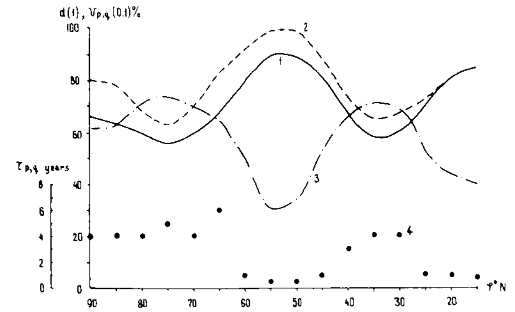

Fig. 4. Parameters of stochastic models of mean zonal air temperature: 1,2—relative prediction errors $d_{p,q}(1)$ and $d_{1,0}(1)$ corresponding to models ARMA(p,q) and AR(1); 3—relative contribution $v_{p,q}(1)$ of low frequencies to the spectrum of MZAT; 4—limits of statistical predictability $\tau_{p,q}$.

high latitudes and decreases to about 0.2 °C south of 50° N. At temperate latitudes, the rms prediction error amounts to three or four tenths of one degree centigrade. The relative one-step prediction error $d_{p,q}(1)$ totals about 60 or 70% and comes to 80 or even 90% at temperate and low latitudes, where the values of $v_{p,q}(0.1)$ are comparatively small (see Fig. 4). The limits of statistical predictability, in the above sense, reach up to 5 or 6 years at 30°–40° N and at latitudes higher than 60° N and drop to 1 year or less at temperate and low latitudes (Fig. 4).

4. Discussion

The variations of MAAT at *individual stations* are practically unpredictable from their past behaviour while their typical spectrum decreases rather slowly with frequency and, as a rule, contains no statistically significant maxima. The position of the maxima on the frequency axis varies from station to station inside a wide frequency range, with no peaks at $f = 0.09$ cpy ("solar cycle"); moreover, only one spectral estimate (at Jena) contains a peak at $f = 0.17$ cpy (close to "double solar cycle"). Thus, there is no evidence of any "solar influence" in the temperature variations.

An optimal model for the MAAT series is distinct, as a rule, from a first-order Markov sequence AR(1), but if the optimal model is changed to its respective approximation with a first-order autoregressive model AR(1), the temperature predictability remains practically unchanged (see the last column in Table 1). This means that the spectral peaks, if any, are not important in the energy budget of temperature variations. All this agrees with the results of earlier experimental studies (Monin and Vulis, 1971; Monin, 1972; Poljak, 1975, 1979; Privalsky, 1976, 1977a, b) and with a stochastic climate model (Hasselmann, 1976). However, *mean zonal air temperature* behaves in a quite different manner. Here, as a rule, the RPE with a one-step lead time amounts to less than 80% and the limits of statistical predictability come to several years, while the spectral energy is concentrated at low frequencies and several spectra contain statistically significant peaks. From the spectral point of view, this relatively high statistical predictability may result from either the predominant low-frequency contribution or from the presence of spectral peaks, or both. In order to describe the rôle of each of these factors quantitatively, the statistical analysis of the results given in Table 2 seems appropriate as a first step. As seen from Fig. 4, the one-step RPE is closely related to the low-frequency contribution $v_{p,q}(0.1)$. Indeed, the correlation coefficient between these two variables, estimated for the 16 pairs of $d_{p,q}(1)$ and $v_{p,q}(0.1)$, that is, for all 16 zones, amounts to −0.97. In other words, the amount of spectral energy contained in the low-frequency range is responsible for 95% of the one-step RPE variation. The linear regression equation between $d_{p,q}(1)$ and $v_{p,q}(0.1)$ is

$$d_{p,q}(1) = 117 - 0.80\, v_{p,q}(0.1) \qquad (5)$$

Thus, the spectral peaks, if any, do not affect the RPE $d_{p,q}(1)$. This result also seems to hold true for the limits of predictability $\tau_{p,q}$, though the low-frequency contribution $v_{p,q}(0.1)$ is responsible for only 75% of the LISP variations. Indeed, the spectral peaks are obviously not important when the LISP value is small (e.g., at 55° N). As for those latitudes where the LISP $\tau_{p,q}$ are relatively large, the rôle of the spectral peaks can be assessed by comparing the optimal AR(p) model whose spectrum contains peaks, with an appropriate ARMA(p,q) model having a monotonous spectrum. Thus, variations of MZAT at 85° N can be "forcibly" approximated by a mixed model ARMA(1, 1) with autoregressive and moving average parameters 0.91 and 0.61, respectively.

(This can be carried as a first approximation because the values of AIC(7,0) and AIC(1,1) for this time series differ insignificantly.) The spectrum $s_{1,1}(f)$ is monotonous (it closely resembles the spectra $s_{1,1}(f)$ at 75° N and 70° N, Fig. 3) but statistical predictability of MZAT by this ARMA(1,1) model turns out to be practically the same for both models. Indeed, the RPE $d_{7,0}(1) = 64\%$, $d_{1,1}(1) = 67\%$ while the LISP $\tau_{7,0} = 3.8$ years and $\tau_{1,1} = 3.4$ years. (A simpler ARMA(1,1) model for this time series is unacceptable because the estimates of its parameters are closely correlated and the correlation function of its residuals differs from zero more significantly than that of the AR(7) model.) Clearly, this approach to the estimation of low-frequency components and the spectral maxima contribution to the limits of statistical predictability is rather conditional, but at least it helps in explaining the results contained in Table 2. It should be noted that the criterion $\tau_{p,q}$, as it is given here, is a somewhat subjective measure of predictability, since it depends on the RPE level which is set equal to 0.8. On the other hand, the behaviour of $\tau_{p,q}$ with latitude remains qualitatively the same when this level is increased to 0.9.

Note also that the high statistical predictability of MZAT is indeed relative. Actually, the absolute rms prediction error is large (not less than 0.75 σ_T) even at a 1-year lead time, so that the 90% confidence interval for the predicted temperature equals or exceeds the standard deviation of temperature σ_T, even at latitudes where the relative error $d_{p,q}(1)$ is minimal. In most cases, the optimal model for the MZAT time series differs significantly from the first-order Markov sequence AR(1). If a first-order Markov model is adopted (that is, if it is assumed in advance that $p = 1$, $q = 0$, and the parameters of the model are estimated), the resulting model will disagree with the optimal one. Thus, as is seen from Table 2, the RPE $d_{1,0}(1)$ that corresponds to this "forced" Markov approximation, will exceed the errors $d_{p,q}(1)$ almost everywhere, while the LISP $\tau_{1,0}$ is proved to be smaller than the limit $\tau_{p,q}$. From this point of view, the Markov approximation can hardly be regarded as satisfactory. If, on the other hand, one still wishes to describe fluctuations in MZAT with a first-order Markov sequence, the desired approximation can be achieved in several ways. Specifically, one may impose the requirement of equal predictability limits $\tau_{1,0} = \tau_{p,q}$ or equal RPE $d_{1,0}(1) = d_{p,q}(1)$ for the optimal model ARMA (p,q) and its first-order Markov approximation AR(1). This will obviously oversimplify the optimal model (in particular, all spectral peaks will be lost). As seen from Table 2, this approach is feasible at several low and temperate latitudes, but in most cases the optimal and Markov models will be distinct in this sense too.

Statistical properties of MZAT averaged over several latitudinal zones are given in Table 2. The orders of the optimal autoregressive models are seen to be rather high for all averaging scales except for the lowest latitudinal zones, where the best choice is the first-order Markov sequence AR(1). In other words, it is the variations of air temperature at high and temperate latitudes which are of major importance in determining the model order. A similar effect is observed for other statistical parameters of zonally averaged MZAT shown in Table 2 except for the mean value $\bar{T}$ and variance σ_T.

The spectrum of mean annual air temperature averaged over the northern hemisphere quickly decreases with frequency in the low-frequency range and contains a peak at $f \sim 0.2$ cpy statistically significant at a low confidence level of about 0.6. This spectral peak is not important because the major part of the energy belongs to the low-frequency range of the spectrum, thus causing a relatively high LISP of the temperature variations. As seen from Table 2, the relative contribution of low frequencies increases as the scale of spatial averaging is increased. This enhancement of low frequencies results from the predominant rôle played by "slow" components in the temperature spectra in most latitudinal zones and, as has been found by carrying out the necessary computations, from a relatively high coherence between low-frequency components in different zones. Hence, when several MZAT time series are averaged, high frequencies are damped. Physically, this high statistical predictability of year-to-year fluctuations in MZAT is probably caused by the smoothing of short-term "weather-induced" fluctuations which serve as the input to the climatic system (Hasselmann, 1976). A similar situation is observed for some other elements of the system, e.g., fluctuations in the water levels of terminal lakes or the salinity of inland seas (Privalsky, 1977b, 1980). By and large, the results obtained in this study confirm the suggestion (Monin, 1972) that spatial averaging may lead to a better statistical predictability, as compared with the predictability of individual processes.

5. Conclusions

Variations of mean annual air temperature at individual stations can be described, to a good approximation, by a first-order Markov sequence with a small regression parameter. Consequently, their statistical predictability is poor. Spatial averaging of air temperature leads to more complicated models and to a better statistical predictability of temperature. In particular, an approximation with a first-order Markov sequence proves to be optimal only at low latitudes while, as a rule, the optimal models are more complicated and have predictability limits up to 4 or 5 years. This relatively high statistical predictability of MZAT stems from the prevalence of slow components in the temperature spectra.

These conclusions agree only partially with the results of earlier experimental studies or with the stochastic climate model proposed by Hasselmann (1976). Still, though the errors of the least-squares temperature prediction are rather high, it seems reasonable to look for physical models which would explain the relatively complicated statistical structure and high predictability of zonally averaged air temperature. It should be noted here that at latitudes lower than 85° N, the behaviour of RPE $d_{p,q}(1)$ with latitude, as is shown in Fig. 4, closely resembles that of the net poleward transport of heat and potential energy in the atmosphere, as is given in Lorenz (1967). If this resemblance is not accidental (the curves have a rather simple form) it might mean that the statistical predictability of MZAT is of a "local" character: it is higher at those latitudes where the transport of heat and energy is minimal and decreases as the values of meridional transport increase. This fact seems to deserve a closer study.

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