Russian Meteorology and Hydrology *Meteorologiya i Gidrologiya*
No. 7, pp. 59-68, 2003 *UDC 556.16*

STUDY OF GENERAL EFFECTS OF RIVER RUNOFF VARIATIONS

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Time series of monthly mean water discharges from some rivers of Europe and the European part of the former USSR are analyzed. The aim of the analysis is to study the effects of general variability of the monthly mean river runoff which arise simultaneously in joint processing of the time series. A river system over large areas coupled with the atmospheric circulation, which affects the river runoff regime, can be considered as a large distributed nonlinear dynamic system. Therefore, it is interesting to study probable effects of interactions within this system. The effects of general variability (coherence) are determined using two procedures: by estimating the evolution of the Hurst constant for different rivers and by estimating the change in the spectral measure of coherence of variations in the specified frequency range. The spectral measure is calculated as a product of component-wise canonical coherences of a multivariate spectral matrix. As a result of analysis, low-frequency effects of general variability are found. Based on the comparison with spectral characteristics of the reconstructed winter mean temperatures for the last 1500 years, a hypothesis of the climatic origin of these variations is proposed.

INTRODUCTION

One of the main objectives of hydrology is to explain the mechanism of long-period runoff variations, to choose an appropriate class of mathematical models, and to verify a specific model on the basis of available, usually scarce, information on river runoff. The interest in these problems is due to their evident practical significance (numerous aspects of water resources management) and to the obvious connection with global climatic processes in the atmosphere and hydrosphere as a whole.

Traditionally, the corresponding time series are the object of the application of different statistical data analysis methods [1, 5, 6, 12, 14, 15]. It should be noted that the attempts aimed at a deterministic description of long-term runoff variations have not been successful so far, although on the conceptual level the connection of runoff with global climatic changes on different scales (from geological to synoptic) is obvious. It seems likely that the interaction between natural processes in the ocean-atmosphere-land system is almost reasonably described only by stochastic models of interaction between individual components.

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Since the results of statistical analysis of time series of hydrological characteristics are practically important, the approach used in engineering hydrology to construct probability models was based on the so-called sparseness principle. This means that one seeks to provide the most concise description of the processes which takes into account the main effects of the basic influencing characteristics. Weak effects not affecting the solution of a given engineering problem were not taken into account. For example, the possibilities of creating regulated reservoirs on rivers are always limited and, thus, a reservoir accumulates (redistributes) runoff only for a few previous years, but more often within a year. Therefore, the spikes with large shifts of autocorrelation functions were usually neglected due to their statistical unreliability. The models recommended for use in water management, as a rule, belonged to a class of stationary Markov processes (with extensions to the non-Gaussian case).

There are, however, other problems for which long-period runoff variations are very important. One of these problems is to describe water level variations in a closed (drainless) basin, such as the Caspian Sea unique in its dimensions. Water level variation in the Caspian Sea integrally allows for the decadal runoff of inflowing rivers. In this case, it is very important to be confident about the right choice of mathematical (stochastic) models.

Stochastic runoff models can hardly be further developed based only on the individual processing of short (about 100 years) observational series. One of the possible ways is to determine some general effects in runoff variations, which, being reliably supported by the hypothesis of data combination, would allow an inference about a new frequency structure of river runoff time series.

This paper considers the time series of monthly mean water discharges in several rivers of Europe and the European part of the former USSR. The aim is to study the effects of general variability of the monthly mean river runoff that arise simultaneously in all the time series analyzed. The effects of general interaction between the elements in the large systems have recently drawn much attention in connection with the study of the properties of nonlinear dynamic systems and determinate chaos [9, 10]. The river system covering large areas and the atmospheric circulation affecting the runoff regime can also be considered as a large distributed nonlinear dynamic system. Therefore, the study of possible interaction effects in this system is of interest. The effects of general variability (coherence) were identified in two ways: by estimating the evolution of the Hurst constant for different rivers and by estimating the change in a spectral measure of coherence of variations in the specified frequency range, which is calculated as a product of component-wise canonical coherences of a multivariate spectral matrix. These methods were tested earlier in geophysical monitoring problems [2-4].

The estimates of all characteristics were calculated in a 30-year moving time window. The choice of this length of the time window is determined by methodological considerations, since it is about one- third of the length of the available time series (corresponding to the minimum at which the variability of statistical properties can be traced). Moreover, it is large enough to average the influence of the known climatic factors, for example, the 11-year solar cycle. From the point of view of statistical stability, 30 years is certainly a critical length. But regrettably, the available observational series of water discharge make it impossible to extend this length.

It should also be emphasized that although the lengths of the analyzed time series are relatively small (about 100 years) compared with the 40-50-year periods of the effects the authors seek to identify, the procedure used is essentially based on estimating the general modulating properties of the series with the major "carrying" period of one year. Variations at the one-year period are statistically significant with the 30-year time window. Therefore, the estimates of variability of the coherent behavior effects in the vicinity of the one-year period are statistically justified by the available sample sizes, unlike, for example a direct estimate of power spectra at the 40-50-year periods.

The analysis made it possible to identify low–frequency variations in coherence measures with characteristic 40–50–year periods. The variations are compared with the variations in global temperature which has a dominant period of 54 years over the last 1000 years. A close coincidence of the periods suggests a hypothesis of a hidden low-frequency climatic component in river runoff variations.

INITIAL DATA

Two groups of the time series were considered. The first group comprises monthly mean discharges for seven rivers: the Oka, Northern Dvina, Loire (France), Glomma (Norway), Danube (upper reach, Germany), Elbe (upper reach, Czech Republic), and Vistula (Poland). The second group consists of monthly mean discharges for nine rivers measured at observation points on the territory of the former USSR in European Russia, Belarus, and Ukraine. One of the rivers, the Oka, is common for the two groups.

In choosing the rivers for the two groups, we were guided by the following considerations. The first group includes rivers under different climatic conditions (zones of both rain and snow feed); the second group, rivers under almost the same conditions (in the zone of rapid spring melt of snow). The fact that one river, the Oka, is common for the two groups is associated with a good representativeness of information about its water regime (long instrumental records and the absence of large hydraulic structures). In the two groups, the Oka represented the runoff regime typical of the midlatitudes of Russia. All the rivers are located in the region of action of the Atlantic cyclones and, in this respect, they are in one global climatic zone.

The time of the start of observations for various time series differs widely. If the analysis method required joint processing of all series (spectral coherence measure), the initial time was chosen common and coincident with September 1901. The time of the end of observations coincided with December 1979 for the first group and with December 1984 for the second group. In a joint spectral analysis of time series of the two groups (taking into account the common Oka River), the right end of the processed time interval coincided with December 1979.

Runoff observation points were chosen with regard to the following conditions: the number of gaps is minimal (maximum length is not greater than two years), and the water discharge does not depend on the operation of hydraulic structures (i.e., not regulated as much as possible). Small gaps were filled in depending on the features of the time series on either side of the missing interval of the same length: for each month with missing data, the water discharge value was taken in the same month on the left and on the right of the interval ends. This filling of the gaps retained the spectral structure of the time series. Since the intervals with missing data were not long (not greater than 24 monthly means) and the analysis was conducted in the 30-year moving time window (360 values), the influence of the gaps on the final result was not strong. This statement was checked by introducing artificial gaps of specified length, by filling them according to the above rule, and by comparing the initial results and the artificially distorted data.

The method used for filling the gaps is probably far from optimal, but its quality proved to be quite satisfactory. Besides, the selection of observation points according to the criterion of the minimum number of gaps is a decisive factor reducing their influence. Other more sophisticated methods, for example, those using water discharges in the nearby rivers similar in water regime (without gaps of records), were often impossible to apply because the observations were most often absent over vast territories and this was connected with military operations.

METHOD OF ANALYZING THE EVOLUTION OF THE HURST CONSTANT

The method of the Hurst constants, or the RS method, is most common in analyzing river discharge data [9, 12, 14, 15]. The Hurst constant is the reduced range (difference between the maximum and minimum sample values) characterizing both the local correlation properties and the low-frequency behavior of the time series. We describe briefly the Hurst method's modification applied here.

Let $\xi(t)$ be the analyzed time series; $t = 1,..., N$; $L \le N$ is the length of the moving time window; τ is the number of the count of the right end of the moving window, i.e., moments t are, considered that satisfy the condition $(\tau - L + 1) \le t \le \tau$; λ is the length of the internal time window used inside the current major time window for averaging. We consider the internal window lengths satisfying the condition $\lambda \le L/5$. Let

$$\bar{\xi}^{(\tau)}_{\lambda,s} = \frac{1}{\lambda}\sum_{t=1}^{\lambda}\xi(s+t-1) \tag{1}$$

be the sample estimate of the mean value in the interval $[s, s+\lambda-1]$ of length λ counts, which lies inside the major time window $(\tau - L + 1) \le s \le \tau - \lambda + 1$. The next step is to calculate the deviations from the mean value (1)

$$\Delta\xi^{(\tau)}_{\lambda,s}(t) = \xi(t) - \bar{\xi}^{(\tau)}_{\lambda,s} \quad \text{for} \quad t \in [s, s+\lambda-1], \; s \in [\tau - L+1, \tau-\lambda+1]. \tag{2}$$

Let the accumulated sum of deviations (2) be equal to

$$x^{(\tau)}_{\lambda,s}(t) = \sum_{u=1}^{t}\Delta\xi^{(\tau)}_{\lambda,s}(u) \quad \text{for} \quad t \in [s, s+\lambda-1], \; s \in [\tau - L+1, \tau-\lambda+1]. \tag{3}$$

Then

$$R^{(\tau)}(\lambda, s) = \max_t x^{(\tau)}_{\lambda,s}(t) - \min_t x^{(\tau)}_{\lambda,s}(t)$$

$$\text{for} \quad t \in [s, s+\lambda-1], \; s \in [\tau - L+1, \tau-\lambda+1], \tag{4}$$

$$(\sigma^{(\tau)}(\lambda, s))^2 = \frac{1}{\lambda}\sum_{t=1}^{\lambda}(\Delta\xi^{(\tau)}_{\lambda,s}(t))^2, \tag{5}$$

where

$$RS^{(\tau)}(\lambda) = \frac{1}{(L-\lambda+1)}\sum_{s=\tau-L+1}^{\tau-\lambda+1}\frac{R^{(\tau)}(\lambda,s)}{\sigma^{(\tau)}(\lambda,s)} \tag{6}$$

is the mean value of the range (4) scaled by dividing by the standard deviation (5).

According to the empirical Hurst law [12], the following relation is valid for many natural processes:

$$\log(RS^{(\tau)}(\lambda)) \sim H(\tau)\log(\lambda), \tag{7}$$

where $H(\tau)$ $(0 < H(\tau) < 1)$ is the so-called Hurst exponent estimated for the current major time window with the right-end coordinate τ. For usual and for general Brownian processes, formula (7) is accurate, with the following formulas being true:

$$S_{\xi\xi}(\omega) \sim \omega^{-(1+2H)} \text{ at } \omega \to 0, D = 2 - H, E\{|\xi(t+\delta) - \xi(t)|^2\} \sim \text{const}\,\delta^{2H}. \tag{8}$$

Here $S_{\xi\xi}(\omega)$ is the generalized power spectrum, ω is the frequency, D is the fractal dimension of the generalized Brownian curve, and E is the sign of mathematical expectation [9, 15]. The quantity $H(\tau)$ can be estimated by linear regression between

$$\log(RS^{(\tau)}(\lambda)) \text{ and } \log(\lambda), \; 1 < \lambda \le L/5$$

using the least-squares method. The meaning of the estimate of the Hurst constant evolution is that its value is a certain integral characteristic of the degree of variability of the process in the time window, or conservativeness, the so-called persistence of the process. The larger the Hurst constant, the more low frequency and more conservative the process.

METHOD OF ANALYZING THE EVOLUTION OF A SPECTRAL COHERENCE MEASURE

A method of identifying the time intervals and frequency bands of the increasing general variability of scalar components of a multivariate time series is briefly described below. Originally, the method was developed for searching for precursors of severe earthquakes from geophysical monitoring data [2].

The ordinary coherence spectrum of two processes can be non-strictly defined as the square of the correlation coefficient of these processes at the frequency ω [13]. Canonical coherences are a generalization of the concept of the coherence spectrum for the situation when, instead of a pair of scalar time series, it is necessary to study the relation at different frequencies between the two vector time series, the *m*-dimensional series $X(t)$ and the *n*-dimensional series $Y(t)$. The value $\mu_1^2(\omega)$, called a square of the modulus of the first canonical coherence of the series $X(t)$ and $Y(t)$, which in this case replaces the usual coherence spectrum, is calculated as the maximum eigenvalue of matrix [7, 11]

$$\mathbf{U}(\omega) = S_{xx}^{-1}(\omega)\, S_{xy}(\omega)\, S_{yy}^{-1}(\omega)\, S_{yx}(\omega)\,. \tag{9}$$

Here t is the discrete time of consecutive counts; $S_{xx}(\omega)$ is the $m\times m$ spectral matrix of the time series $X(t)$; $S_{xy}(\omega)$ is the cross-spectral rectangular matrix of size $m\times n$; $S_{yx}(\omega) = S_{xy}^{\mathbf{H}}(\omega)$; $\mathbf{H}$ is the Hermitian conjugation sign.

We introduce the concept of component-wise canonical coherence $\nu_i^2(\omega)$ of the *q*-dimensional time series $Z(t)$ as the squares of the modulus of the first canonical coherence in the case where the *i*-th scalar component of the *q*-dimensional series $Z(t)$ is taken as the series $Y(t)$ in (9) and the $(q–l)$-dimensional series consisting of the remaining components is taken as the series $X(t)$. Thus, $\nu_i^2(\omega)$ characterizes the coherence at the frequency ω of the *i*-th component variations with variations of the totality of the remaining components. The introduction of component-wise canonical coherence allows us to determine one more frequency-dependent statistic $\kappa(\omega)$, which characterizes the coherence of variations of all the components of the vector series $Z(t)$ at the frequency ω:

$$\kappa(\omega) = \prod_{i=1}^{q} \nu_{\mathrm{i}}(\omega)\,. \tag{10}$$

Note that due to construction, the value $\kappa(\omega)$ belongs to the interval [0, 1] and the closer the corresponding value to unity, the stronger the relation between variations of the components of the multivariate time series $Z(t)$ at the frequency ω.

To estimate the time variability of the interaction between the recorded processes, it is necessary to make calculations in a moving time window of specified length. Let T be the time coordinate of the window of length L counts. By calculating spectral matrices for the sample in the time window τ, we obtain a two-parameter function $\kappa(\tau,\omega)$. The spikes of $\kappa(\tau,\omega)$ will be determined by frequency bands and time intervals of the increase of general variability of the jointly analyzed processes.

To implement this algorithm, the spectral matrix $S_{zz}(\omega)$ of size $q\times q$ has to be estimated in each time window. Below a preference is given to the vector autoregression model [16]. The method consists of estimating parameters of the model

$$Z(t) + \sum_{k=1}^{p} \mathbf{A}_k\; Z(t-k) = e(t)\quad . \tag{11}$$

Here $\mathbf{A}_k$, denotes the autoregression parameter matrices of size $q\times q$; p is the order of autoregression; $e(t)$ is the *q*-dimensional time series of identification residuals, which is supposed to be a sequence of independent Gaussian vectors with the zero mean and the unknown covariance matrix **P**. It should be noted that model (11) was constructed after eliminating the general linear trend and normalizing each scalar component by unit variance. These operations are performed independently in each time window and for each scalar component of the multivariate series. They are intended to eliminate the influence of different scales of the series. The matrices $\mathbf{A}_k$ and **P** are estimated using the Durbin-Levinson recurrence procedure [16], for which the sample estimates of covariance matrices, are to be calculated preliminarily.

The estimate of the spectral matrix is given by

$$S_{ZZ}(\omega) = F^{-1}(\omega)\,\mathbf{P}\,F^{-\mathbf{H}}(\omega) \tag{12}$$

where $F(\omega) = I + \sum_{k=1}^{p} \mathbf{A}_k \exp(-i\omega k)$.

Estimate (12) has a good resolution in frequency for short samples and so it is preferable for estimates in the moving time window than, for example, nonparametric estimates through the averaging of multivariate periodograms. There are no reliable formalized procedures for choosing the order of autoregression *p*. In calculations, *p* was chosen by a trial-and-error method as the minimum value for which a further increase would not produce substantial changes in the major elements of variability of the measure $\kappa(\tau,\omega)$. Below, the value $p = 3$ is used everywhere.

RESULTS

Figure 1 shows the diagrams of changes in the estimates of the Hurst constants in the 30-year moving time window for the data from the first and second data sets. For the rivers in the first group, we can note the presence of the common element in all the curves, except the Northern Dvina, i.e., the increase in the Hurst constant for the moving windows centered at 1920-1940. This feature has a period of about 40-50 years and is present in all the time series with a different degree of strength, despite the difference in the geographic position. Thus, there is evidence of the presence of some general component in the time series of river runoff.

For the second-group rivers, Fig. 1 also shows a quasi-periodicity of 40-50 years; however, unlike the rivers from the first group, this quasi-periodicity is not synchronous in all the series. Of the eight rivers in the second group (except the Oka), five rivers (the Desna, Sozh, Western Dvina, Belaya, and probably the Volga) have curves of the Hurst constant evolution with the obvious general features. The peak of the curves falls on nearly the same period as for the first group, the mid-1930s. For the remaining three rivers, the Hurst curves have shifted peaks.

In comparing the variations of the Hurst constants, we restricted ourselves to a purely visual analysis, without using any quantitative criteria, such as calculations of correlation coefficients. The reason for that is as follows. The curves have a very low-frequency character in the time intervals in which they are estimated. In this case, the estimates of correlation coefficients are known to be strongly biased and can be changed arbitrarily owing to a very small phase shift for low frequencies. Therefore, a purely qualitative visual analysis in this case is a more objective instrument. Certainly, we had to reject a quantitative comparison of the Hurst constant variation curves because of the lack of data.

For a further multivariate spectral analysis, the third set of time series was created that included data for the rivers subjectively having evident similar features in the Hurst constant curves. These are ten rivers: the Loire, Vistula, Elbe, Danube, Glomma, Oka, Western Dvina, Sozh, Desna, and Belaya. This selection has inevitable features of a subjective choice. At the same time, the time series of the third group are equally represented by the rivers of both Western and Eastern Europe, and the evolution of the coherent component in their variations reflects certain objective changes of the water regime over a large region. Moreover, there is also a methodological restriction on the volume of the simultaneously analyzed time series: the estimates of spectral matrices

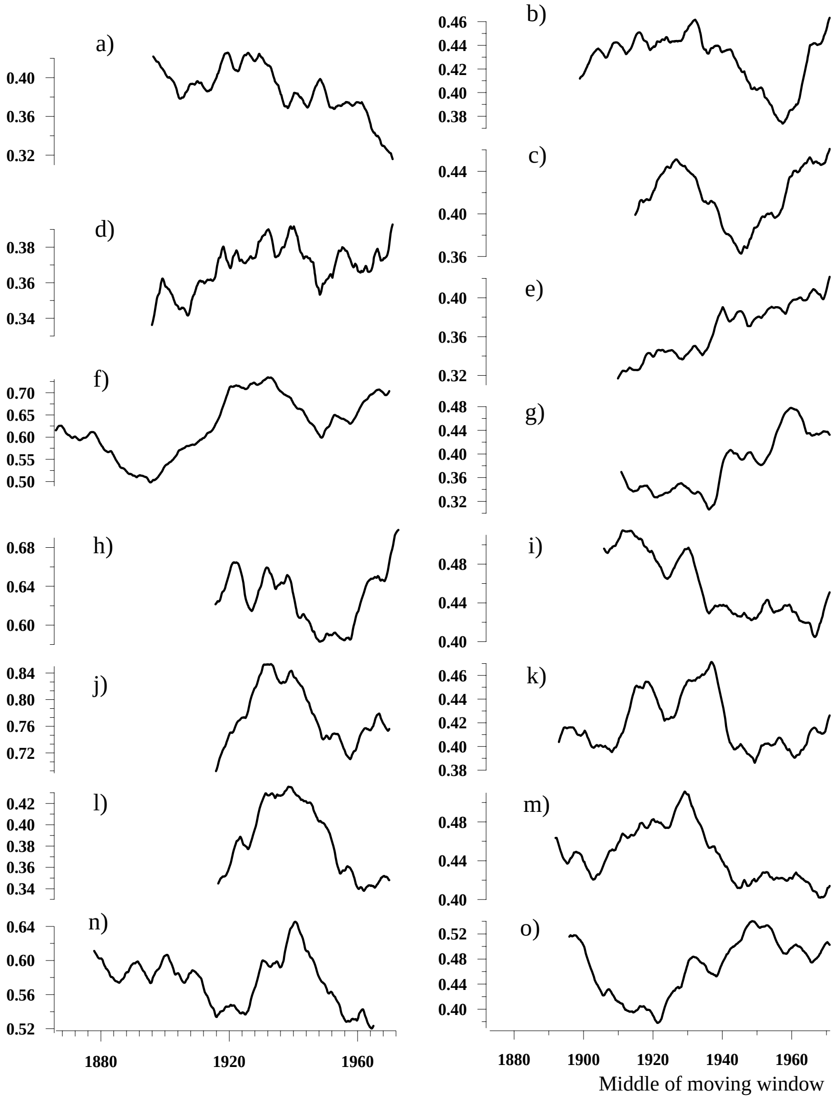

Fig. 1. Estimates of the Hurst constant evolution in the 30-year moving window for the first (a, d, f, h, j, l, n) and second (b, c, e, g, i, k, m, o) data sets, except the Oka. (a) the Northern Dvina; (b) Desna (the town of Chernigov); (c) Sozh (the town of Gomel); (d) Oka; (e) Don (town of Liski); (f) Elbe; (g) Unzha (Makariev Monastery); (h) Vistula; (i) Volga (the town of Zubtsov); (j) Danube; (k) Belaya (the city of Ufa); (l) Glomma; (m) Western Dvina (the town of Vitebsk); (n) Loire; (o) Tikhvinka (the village of Gorelukha).

are to a greater extent subject to purely statistical errors when the number of the simultaneously estimated parameters grows.

Figure 2 shows the results of the multivariate spectral analysis and their comparison with the data in Fig. 1; note that the procedures themselves are fundamentally different. Figures 2a-2c represent two-dimensional diagrams of $\kappa(\tau,\omega)$ for the indicated parameter values and Figs. 2d-2f show the maximum value (in frequency): $\rho(\tau) = \max \kappa(\tau,\omega)$. These one-dimensional diagrams provide a side view of the top plane diagrams if they are presented as a three-dimensional relief. It is seen in Figs. 2a-2c that the maximum coherence measure is focused in the vicinity of the one-year period of seasonal variations. In other words, two-dimensional diagrams contain one major ridge of the maximums of the value $\kappa(\tau,\omega)$,

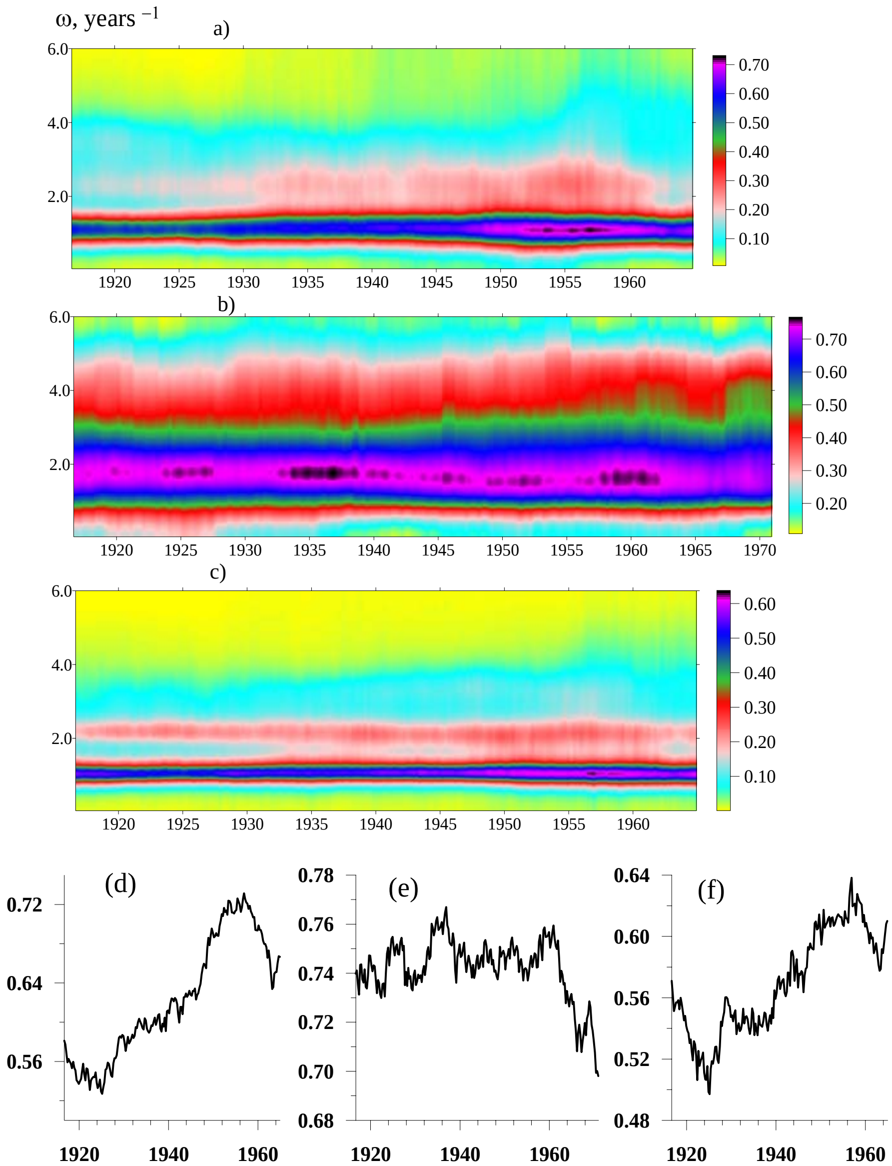

Fig.2. Estimates of the evolution of the product of component-wise canonical coherence for (a) the first, (b) second, and (c) third sets of time series, respectively, and their maximum frequency products for (d) the first, (e) second and (f) third data sets, respectively. The length of the time window is 360 values (30 years), shift is 3 counts, autoregression order equals 3.

which justifies a subsequent transition to one-dimensional diagrams of its frequency maximums.

According to Figs.2a and 2d, the maximum correlation (at the frequency ~ 1 year^{-1}) increases with time and reaches 0.73 by 1955, which corresponds to the correlation coefficient $\sqrt{0.73}$ =0.85. Figure 2b shows the significant coherence of water discharge variations in a very wide frequency band in the vicinity of the seasonal crest. This is also seen in the diagram $\rho(\tau)$ (Fig.2e): the variation scale is small and the mean value corresponds to a coherence of 0.74. This is likely to be indicative of the common climatic conditions regulating water discharges in the rivers of the European part of the former USSR. For the first group of rivers (Figs.2a and 2d), these climatic changes (on average over time) are less synchronous.

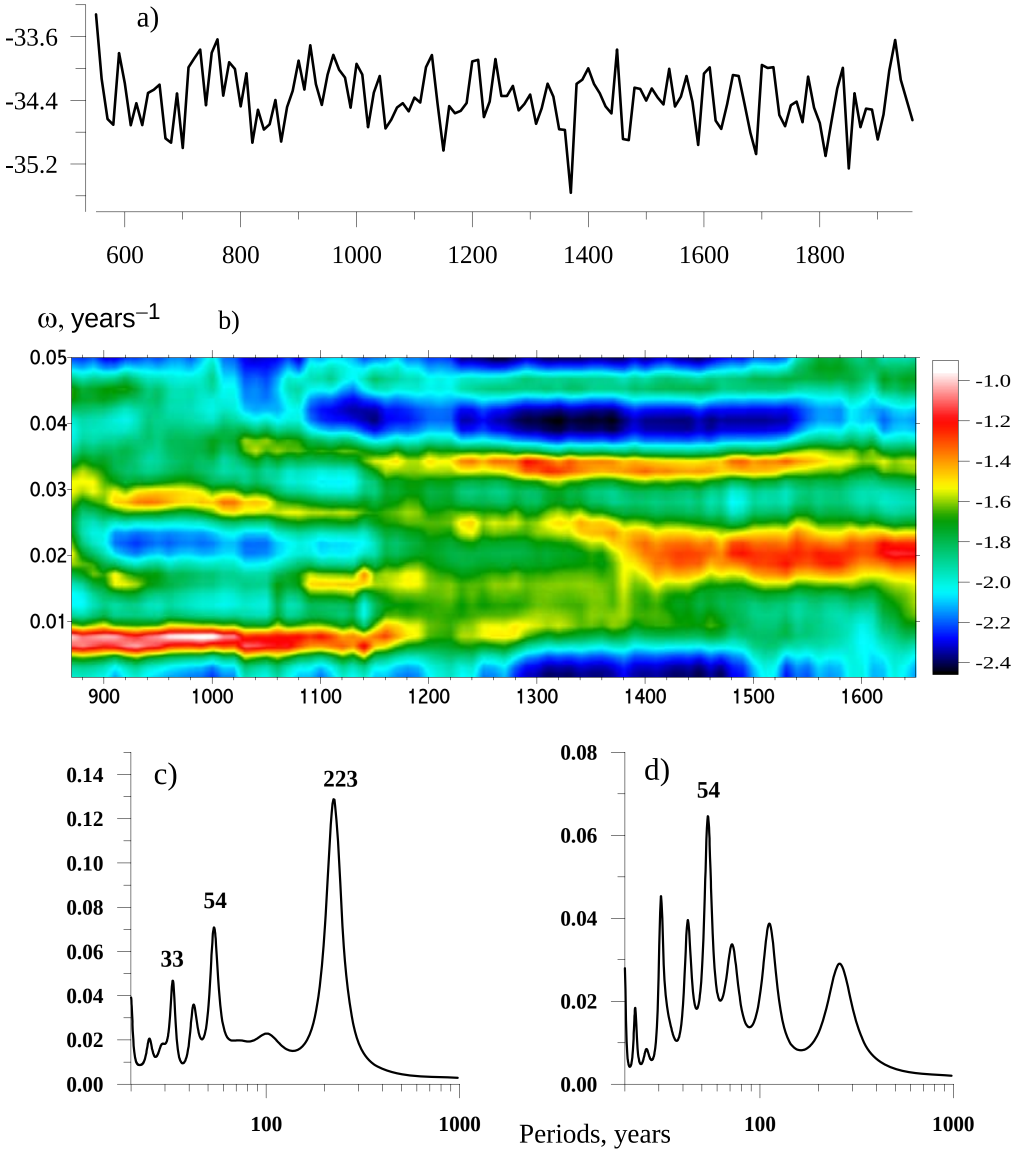

Fig.3. (a) Reconstructed winter mean temperature for successive 10-year intervals, (b) evolution of the decimal logarithm of the power spectrum of the series shown in Fig.3a (estimate in the moving time windows of length 64 values, 640 years), and estimates of the power spectrum of reconstructed temperatures for (c) the whole sample and (d) for the past 1000 years.

Of most interest are the diagrams in Figs.2c and 2f because they reflect the results of data processing for the ten rivers located in very different climatic and geographic conditions and actually covering the whole of Europe. Despite these differences, the rivers are similar in having the common variability of the Hurst constant. The spectral coherence measure in Fig. 2c differs primarily in a clearly pronounced six-month ridge, which is seen neither in Fig.2a nor in Fig.2b. The diagram $\rho(\tau)$ in Fig.2f is very similar to that in Fig.2d, except that its 40-50-year periodicity is more pronounced. Moreover, the general coherence level became lower, which is certainly to be expected in processing the series with a priori large differences in variability. Thus, the results of the fundamentally different methods of analyzing the time series do not contradict each other and exhibit the same regularity in runoff variations which has a characteristic time scale of 40-50-years.

CONCLUSIONS AND DISCUSSION

Turning back to the hypothesis of a climatic origin of low-frequency variations in coherence measures of runoff time series, it should be asked whether a similar time scale is present in any climatic data.

Figure 3a presents the annual mean winter temperatures in the Northern Hemisphere reconstructed from the ^{18}O isotope content in Greenland ice kerns [8]. It can be seen that distinct temperature fluctuations with periods from 50 to 100 years were observed during the past 1500 years. One of the periods with high annual mean temperature falls in the 700s-900s (Viking era).

Figure 3b shows a two-dimensional diagram of the evolution of the logarithm of the power spectrum of the time series of reconstructed temperatures that is estimated in the moving time window of length 64 values (640 years). The spectral peak with a period of 50-60 years is dominant in the past 1000 years. Interestingly, the low-frequency rhythm with a period of about 200 years is related only to the initial portion of the time series, from the year 550 to 1450.

Figures 3c and 3d show the estimates of the power spectrum of the time series of reconstructed temperatures throughout the sample and for its latest portion corresponding to the past 1000 years. The estimate of the power spectrum of the time series in Fig.3c yields clear peaks at the periods of 33, 54, and 223 years. The estimate of the 90% confidence interval of spectral values [7, 13] is 0.011. As seen in Fig.3d, the 54-year period prevails in the past 1000 years, which agrees with the frequency-time diagram in Fig.3b.

Thus, the current tendencies in global temperature are characterized by intense harmonics with periods of about 54 years. According to our hypothesis, it is these harmonics that produce low-frequency variations of the coherence measure and variations of the Hurst constant.

The work was supported by INTAS (grant 99-0099) and the Russian Foundation for Basic Research (00-05-65208).

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11 November 2002