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Recognition of "Slow Events" in an Aseismic Region

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INTRODUCTION

This paper presents an algorithm for the analysis of combined observations of variations in low-frequency crustal background processes (with periods of more than 2 hours) intended for the detection of anomalies that are related to simultaneous pattern rearrangements in all processes observed. If data are gathered from a monitoring network covering a considerable crustal area, such a rearrangement may indicate intensification of tectonic energy dissipation in the upper crust, producing such effects as enhanced creep movements, landslide processes, and groundwater migration. These anomalies, called in this paper "slow events", are analogues of ordinary earthquakes in seismically active regions.

Slow events are evidently related to the seismological notion of a "slow" ("quiet") earthquake, which is the limiting case of an ordinary seismic event that is characterized by an extended phase of seismic energy release, producing a lower-frequency spectrum of seismic radiation [Kasahara, 1985; Linde *et al.*, 1996]. Detection of a slow earthquake makes great demands on seismic instrumentation and still remains somewhat extraordinary.

Current models of energy dissipation in the upper crust [Sadovskii and Pisarenko, 1987; Sadovskii, 1989] are largely based on the notions of self-similarity and self-modeling inherent in processes in the lithosphere, which implies that they are essentially similar in both seismically active and aseismic regions and differ only in characteristic frequencies of energy dissipation. Whereas high-frequency dissipation is typical of seismically active regions with high values of the tectonic energy influx, the energy release in aseismic regions with less intense energy fluxes is more gradual and does not excite seismic waves but intensifies slow crustal movements in relatively narrow zones (lineaments). Such intensification may enhance migration of groundwater capable of weakening crustal blocks and promoting corrosion processes, which in turn increases the probability of landslides, occurrence of cracks in large building basements, underground tunnel failures, and corrosion of subway tracks. Moreover, enhanced groundwater migration may result in transportation of radioactive materials to the surface and rise in the level of natural radioactive and electromagnetic background.

The detection of slow events is a very complicated problem (particularly in the megalopolis environment) and requires combined methods of observations and information analysis. A single instrument (strain gage, tiltmeter, or gravity meter) yields an observation series mainly consisting of cultural or meteorological noise. Useful information (or desired signal) can be recovered only from combined statistical analysis of measurements by a set of instruments that record various geophysical fields and/or are located at various observation points. Areas free from cultural noise become progressively smaller, as technological impact zones enlarge. For this reason, development of methods for the most effective elimination of cultural noise from observations is a very significant problem of geophysical data analysis. As distinct from meteorological noise (variations in atmospheric pressure, temperature, humidity, and precipitation), cultural noise cannot be directly measured. Consequently, the only means for its removal is the use of data measured at different points under the assumption that correlation between noise signals at each point is small.

This work presents a method for recognition of slow events, based on the numerical procedures previously developed for the multivariate analysis of diverse geophysical information [Lyubushin, 1993, 1994; Lyubushin, *et al.*, 1997a, b]. The method is exemplified by its application to the construction of a catalog of slow events in Moscow for the time period from 1993 to 1996, based on observations of groundwater level variations in four aquifers.

PROCESSING PROCEDURE

The method of principal components [Brillinger, 1980] consists in the estimation of the spectral matrix $S_{ZZ}(\omega)$ of a multivariate time series $\mathbf{Z}(t)$ whose components are scalar time series of monitored values of various geophysical parameters. Also, a maximum eigenvalue $\lambda_1(\omega)$ of the estimator is calculated. Here, t is discrete time indexing consecutive samples and ω is frequency. In the widely used discrete Fourier transformation, ω represents discrete frequencies $2\pi(t-1)/(N\delta t)$, $t = 1, \ldots, N$, where N is the total number of samples within processing time window and δt is the time discretization (sampling) interval. The maximum eigenvalue $\lambda_1(\omega)$ is the power spectrum of a hypothetical scalar time series $W_1(t)$ (series of the first principal component) obtained from multivariate filtering of the original series $\mathbf{Z}(t)$, with the frequency filter being represented by the eigenvector of the matrix $S_{ZZ}(\omega)$ corresponding to the eigenvalue $\lambda_1(\omega)$. Algorithmically, $W_1(t)$ is calculated in such a way that, for each frequency, the multivariate Fourier transform of $\mathbf{Z}(t)$ is projected onto the eigenvector of matrix $S_{ZZ}(\omega)$, corresponding to the maximum eigenvalue $\lambda_1(\omega)$, and then the inverse Fourier transformation is applied to the projection result. In the case of Gaussian time series, $W_1(t)$ provides maximum information on the common behavior of scalar components of the series $\mathbf{Z}(t)$ [Brillinger, 1980].

Canonical coherences [Brillinger, 1980] extend the notion of squared modulus of a coherence spectrum to the case when the relation between two vector, rather than scalar, time series should be examined as a function of frequency; these are the *m*-dimensional series $\mathbf{X}(t)$ and *n*-dimensional series $\mathbf{Y}(t)$. They may represent measurement results of two different geophysical fields, and the series dimensions (which may be different) are then the numbers of points at which each of the fields is observed. In the given case, the value $\mu_1^2(\omega)$, called the squared modulus of the first canonical coherence of the series $\mathbf{X}(t)$ and $\mathbf{Y}(t)$, stands for the ordinary squared modulus of the coherence spectrum and is calculated as a maximum eigenvalue of the matrix resulting from the product of inverse spectral and cross-spectral matrices [Brillinger, 1980]:

$$U(\omega) = S_{XX}^{-1}(\omega)S_{XY}(\omega)S_{YY}^{-1}(\omega)S_{YX}(\omega). \quad (1)$$

We introduce the notion of canonical component coherences $\nu_i^2(\omega)$ [Lyubushin, 1998a] defined as squared moduli of the first canonical coherence, provided that the series $\mathbf{Y}(t)$ in formula (1) is the *i*th scalar component of the *l*-dimensional series $\mathbf{Z}(t)$, and $\mathbf{X}(t)$ is the $(l-1)$-dimensional series consisting of all other components. Then, the value $\nu_i^2(\omega)$ characterizes the correlation of the variation in *i*th component with variations that are present in all other components at a frequency ω. Introduction of canonical component coherences allows determination of a frequency-dependent statistic $\rho^2(\omega)$ which characterizes the correlation between variations in all components of the vector series $\mathbf{Z}(t)$ at a frequency ω,

$$\rho^2(\omega) = \frac{1}{l}\sum_{i=1}^{l}\nu_i^2(\omega). \quad (2)$$

Lyubushin [1993, 1994] and Lyubushin *et al.* [1997a, 1997b] considered estimates of spectral statistics in a moving time window of a given length. Let τ be the time coordinate within a window *L* samples long. Calculation of diverse spectral matrices for samples within the time window τ yields a family of two-parameter functions

$$\lambda_1(\tau, \omega), \quad \mu_1^2(\tau, \omega), \quad \rho^2(\tau, \omega). \quad (3)$$

A synchronization signal of scalar components of a multivariate time series $\mathbf{Z}(t)$ is defined as paired values of (τ, ω) (i.e., time intervals of τ and frequency bands of ω) for which time–frequency statistics exceed a certain threshold depending on the level of their "background" variations [Lyubushin, 1993, 1994; Lyubushin *et al.*, 1997a, 1997b]. Similarly, the function $\mu_1^2(\tau, \omega)$ defines a synchronization signal for a pair of vector time series. Note that the analysis of the function $\lambda_1(\tau, \omega)$ is actually an extension of the time-frequency analysis, well known in geophysics, to the multivariate case. Lyubushin *et al.* [1997b] applied statistics (3) to the search for strong earthquake precursors from hydrogeochemical observations conducted in the Kamchatka region from 1986 to 1992.

Finally, we introduce the notion of an aggregated signal of a monitoring system [Lyubushin, 1998b]. For this purpose, taking the *i*th scalar components $Z_i(t)$ from the multivariate observation series $\mathbf{Z}(t)$, we filter the $(l-1)$-dimensional series $\mathbf{X}^{(i)}(t)$, composed of the remaining components, under the condition of maximum coherence between the scalar signal $C_i^{(Z)}(t)$ resulting from the filtering and chosen series $Z_i(t)$ at each frequency. This can be achieved if the frequency filter is represented by the eigenvector of matrix (1) in which $Z_i(t)$ and $\mathbf{X}^{(i)}(t)$ stand for $\mathbf{Y}(t)$ and $\mathbf{X}(t)$, respectively; the latter corresponds to the maximum eigenvalue of the matrix (it is easy to show that this eigenvalue is $\nu_i^2(\omega)$). This procedure means that, if the component $Z_i(t)$ contains noise typical only of this series and absent in other components of the series $\mathbf{Z}(t)$, the signal $C_i^{(Z)}(t)$ is free from this noise on the strength of the construction itself. (Usually, such noise has cultural origin or is due to systematic errors of measurements.) On the other hand, the series $C_i^{(Z)}(t)$ preserves all features of the component $Z_i(t)$ that are common to the remaining components of the series $\mathbf{Z}(t)$, which compose the signal $\mathbf{X}^{(i)}(t)$. We call the series $C_i^{(Z)}(t)$ the canonical component of the scalar series $Z_i(t)$.

An aggregated signal $A_Z(t)$ of the multivariate time series $\mathbf{Z}(t)$ is defined as the first principal component of the multivariate series $\mathbf{C}^{(Z)}(t)$ composed of canonical components $C_i^{(Z)}(t)$ of each scalar time series belonging to the original series $\mathbf{Z}(t)$ [Lyubushin, 1998b]. We emphasize that the series $A_Z(t)$ differs from the first principal component $W_1(t)$ of ordinary type. In both cases, the series are obtained from multivariate filtering with the use of the frequency filter represented by the eigenvector of the spectral matrix, corresponding to a maximum eigenvalue of the same matrix. However, such a spectral matrix is represented by the matrix of the original time series $\mathbf{Z}(t)$ in the case of $W_1(t)$ and by the spectral matrix of the series $\mathbf{C}^{(Z)}(t)$ in the case of $A_Z(t)$. Although both filtering procedures extract common components, the aggregated signal $A_Z(t)$ is preferable to $W_1(t)$, because the procedure of its construction completely eliminates individual noise, whereas this may not be the case with the signal $W_1(t)$ especially if the noise includes intense monochromatic components.

It is also important to note that the estimates of spectral matrices and aggregated signal are obtained upon preliminary consecutive operations designed to eliminate the general linear trend, transition to incremental series, and normalization of each scalar component to the unit dispersion. These operations are independently conducted in each processing time window and for each scalar component of a multivariate series. They are performed to remove the effect of different scales of the series processed, which is especially important if the statistic of the maximum eigenvalue $\lambda_1(\tau, \omega)$ of spectral matrix is used. As seen from formula (1), canonical coherences are invariant with respect to both the scale of scalar time series and any nondegenerate linear transformations of the latter. However, preliminary "smoothing" operations are beneficial to the coherences as well, because they reduce the effect of rounding errors which arise due to finite length of numerical format in the computer memory.

Autoregression model parameters of an aggregated signal were estimated with the use of a double moving time window, in order to recognize intervals of intense structural reconstruction in the processes studied. Let $y(t)$ be an aggregated signal of monitoring system with removed low-frequency components (we mean the frequencies whose periods are comparable with the half-length of the moving time window L; for example, they may be longer than $L/(5\delta t)$. If τ is the center of a double moving time window, the sampling times t within this window meet the condition

$$\tau - L \le t \le \tau + L. \tag{4}$$

A scalar autoregression model is constructed for the left- and right-hand halves of window (4):

$$y(t) + \sum_{k=1}^{q} a_k y(t-k) = \eta(t) + d, \tag{5}$$

where q is the autoregression order, a_k are parameters of autoregression, $\eta(t)$ is the identification residual which is Gaussian white noise with an unknown variance s, and d is the static bias parameter. To write model (5) in a more compact form, we introduce auxiliary vectors

$$\begin{aligned} \mathbf{x}(t) &= (-y(t-1), \ldots, -y(t-q), 1)^T, \\ \mathbf{c} &= (a_1, \ldots, a_q, d)^T, \end{aligned} \tag{6}$$

where symbol "T" means transposition. Using (6), model (5) can be written as

$$y(t) = \mathbf{c}^T\mathbf{x}(t) + \eta(t), \quad \langle \eta^2(y) \rangle = s^2. \tag{7}$$

The complete vector of the parameters of model (7) is

$$\boldsymbol{\vartheta} = (\mathbf{c}^T, s)^T. \tag{8}$$

Estimation of model (7) from independent samples that fall into the left- or right-hand halves of double moving time window (4) yields two vectors of parameters (8) $\boldsymbol{\vartheta}^{(1)}$ and $\boldsymbol{\vartheta}^{(2)}$, respectively; for example, for the left-hand half of the window, they are calculated as follows:

$$\begin{aligned} \mathbf{c} &= A^{-1}\mathbf{R}, \quad A = \sum_{t=\tau-L+q}^{\tau} \mathbf{x}(t)\mathbf{x}^T(t), \\ \mathbf{R} &= \sum_{t=\tau-L+q}^{\tau} y(t)\mathbf{x}(t), \end{aligned} \tag{9}$$

$$\begin{aligned} s^2 &= \frac{1}{(L-q)} \sum_{t=\tau-L+q}^{\tau} \eta^2(t), \\ \eta(t) &= y(t) - \mathbf{c}^T \cdot \mathbf{x}(t). \end{aligned} \tag{10}$$

Let $\Delta\boldsymbol{\vartheta} = \boldsymbol{\vartheta}^{(2)} - \boldsymbol{\vartheta}^{(1)}$ be the difference between the vectors of estimates from the left- and right-hand halves of window (4).

The stronger the contrast in the behavior of aggregated signal from the left- and right-hand halves of the window, the greater the difference $\Delta\boldsymbol{\vartheta}$. In order to perform the "weighting" of the vector $\Delta\boldsymbol{\vartheta}$, the matrix defining a metric is taken as a half-sum of Fisher matrices of the type [Rao, 1968]

$$B = \frac{1}{(L-q)}\left(-\frac{\partial^2 \ln(\Phi)}{\partial\boldsymbol{\vartheta}\partial\boldsymbol{\vartheta}}\right). \tag{11}$$

These are matrices of second derivatives of the conditional logarithmic likelihood function of model (7) with respect to parameters, normalized to the number of samples and taken with the minus sign,

$$\ln(\Phi) = -(L-q)\ln(s) - \frac{1}{2s^2}\sum_t (y(t) - \mathbf{c} \cdot \mathbf{x}(t))^2. \tag{12}$$

Let $B^{(1)}$ and $B^{(2)}$ denote matrices (11) calculated from the left- and right-hand halves of moving time window (4), respectively. Then, the nonstationarity measure of the process $y(t)$ in a symmetrical neighborhood of the point τ is

$$r^2(\tau) = \frac{1}{2}(\Delta\boldsymbol{\vartheta}^T B^{(1)} \Delta\boldsymbol{\vartheta} + \Delta\boldsymbol{\vartheta}^T B^{(2)} \Delta\boldsymbol{\vartheta}). \tag{13}$$

Such a metric furnishes a natural dimensionless measure of nonstationarity in the behavior of the signal studied.

Using (9)–(12), it is easy to derive the following formula:

$$\Delta\boldsymbol{\vartheta}^T B \Delta\boldsymbol{\vartheta} = \frac{2(\Delta s)^2}{s^2} + \frac{\Delta\mathbf{c}^T A \Delta\mathbf{c}}{s^2(L-q)} + 2\Delta\mathbf{c}^T \Delta s\left(\frac{2}{s^3}\sum_t \eta(t)\mathbf{x}(t)\right) / (L-q), \quad (14)$$

which is helpful in calculation of statistic (13). Here, $\Delta\mathbf{c}$ and $\Delta\mathbf{s}$ are, respectively, differences of vectors **c** and variances **s**, estimated from the left- and right-hand halves of the moving time window.

Consecutively shifting the time window by one sample and calculating expression (13) for each position of the window center (8), we obtain the time variation τ plot of the nonstationarity measure, so that moments of sharp variation in properties of the process should appear as peaks in $r^2(\tau)$. High-amplitude peaks observed in such a plot constructed for the aggregated signal are evidence that there are time moments at which the patterns of all processes included in the aggregation procedure simultaneously change. In the case of low-frequency background crustal processes, such time moments, henceforth called "slow events," are relevant, for example, to the problem of recognition of "quiet" earthquakes and time intervals of enhanced creep movements of crustal blocks. If synchronous long-term records of variations in background processes are available from a monitoring system that covers a considerable crustal area, calculation of the aggregated signal nonstationarity measure permits the construction of a catalog of slow events in which peak values of nonstationarity measure would characterize the "magnitude" of slow events.

Double time window identification of nonstationarity measure peaks in the behavior of an aggregated signal can be considered a special case of the problem of an abrupt change in a random process [Basseville, 1989] which is solved in an *a posteriori* mode, when fast (real-time) recognition of this disturbance is not critical, whereas exact determination of the disturbance moment and estimation of its intensity are of prime importance.

We emphasize that only the use of aggregated signal ensures reliable recognition of slow events, because evolution of the nonstationarity measure of original time series is controlled solely by local noise, particularly under conditions of an intense technological impact on the geophysical environment.

INITIAL DATA

We consider a four-dimensional series of groundwater level variations measured in wells with the use of filters at depths of 120, 180, 400, and 1000 m. The time interval from 12:00, February 2, 1993 to 23:00, December 30, 1996 (local winter time) provided time series each 34284 hourly samples long. The observations were made by V.A. Malugin and O.S. Kazantseva at two points 40 km wide apart, one in Moscow (area of the Central Institute of Traumatology and Orthopedics, near the "Voikovskaya" subway station) and another in the Zelenyi settlement, Noginskii district, Moscow region. Groundwater level variations were measured in wells 400 and 1000 m deep at the first site and in wells 120 and 180 m deep at the second site. For simplicity, the series are labeled by these depth values: "120," "180," "400," and "1000." Intense cultural noise related to groundwater withdrawals is inherent in the variations in levels 120 and 180. This noise affected most the level-120 variations, because the measuring well is 1.5 km from a pumping station withdrawing groundwater for the needs of surrounding settlements.

Figures 1a–1d plot time series of variations in the groundwater level, with the atmospheric pressure effect removed with the help of the method developed by Lyubushin [1993]. A high-amplitude annual periodicity is observed at the deepest horizon 1000. The level variations plotted in Fig. 1 were measured in the well by a gage with a sensitivity of 0.1 mm H_2O. Note that Lyubushin *et al.* [1997b] analyzed these data to examine a common nonstationary component within tidal frequency bands.

Figure 1e plots the aggregated signal obtained for the four time series studied. Spectral matrices were estimated by using a nonparametrical method including a Fourier transformation, construction of cross-periodograms, and their averaging with the use of a frequency window with a radius of 1024 discrete frequencies. The general amount of the latter being 65536 (a number closest to a power of two and exceeding a series length of 34284), a one-hour sampling interval yields a frequency band of 0.03125 h^{-1}. To suppress the effect of remote frequencies, the series end intervals as long as 1/16 of the total length were smoothed by using a cosine window [Brillinger, 1980].

RESULTS OF THE ANALYSIS

Estimation of nonstationarity measure evolution (13) requires preliminary operations to be performed which should assure local stationarity of a study signal at the center of moving window *L*. In what follows, we will use *L* equal to 336 (hourly) samples, which cover an interval of 14 days. This window was chosen because it completely covers a two-week modulation period of tidal harmonics [Melchior, 1968], thereby precluding this well-studied and fully deterministic factor to be responsible for the inferred peaks of nonstationarity measure.

Furthermore, the series under study were first transformed into incremental series, because all of the ana-

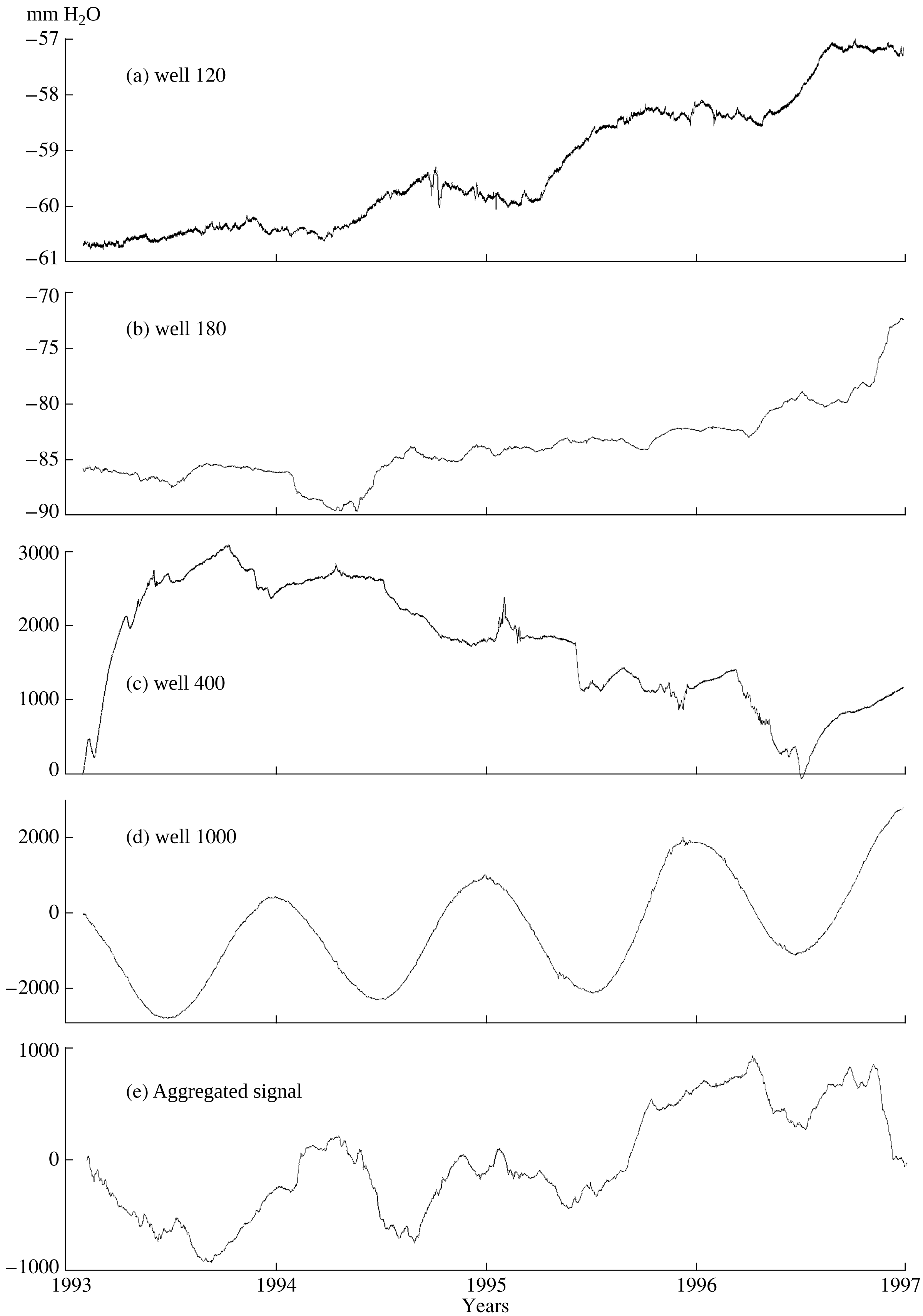

Fig. 1. Plots of (a)–(d) initial time series of groundwater levels with removed effect of atmospheric pressure and (e) their aggregated signal.

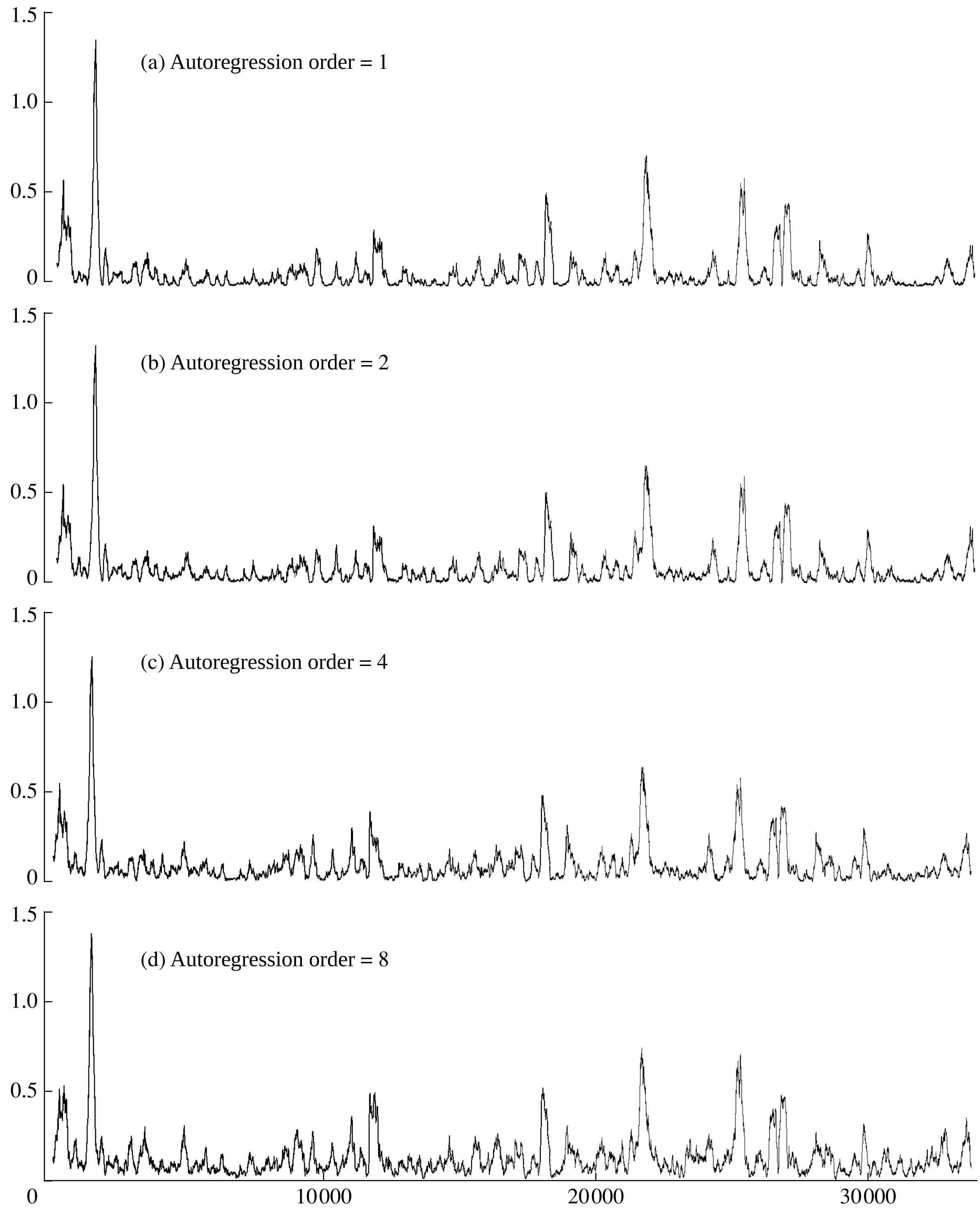

Fig. 2. Variations in the nonstationarity measure of aggregated signal, estimated with the use of a double moving time window 672 h (28 days) long for various orders of autoregression; τ is the time interval between the moment 12:00, February 2, 1993 and the center of the window.

lyzed series are dominated by low frequencies, i.e., their power spectra increase as $\approx\omega^{-\beta}$ with decreasing frequency, where β is about 2.5. This operation decreases the contribution of the lowest frequencies but preserves the dominant of harmonics with periods of 30 to 200 h. Therefore, the next operation was to smooth the spectrum through the application of a first-order filter to each incremental series:

$$y(t) = u(t) - bu(t-1). \quad (15)$$

Characteristics of the most pronounced ($r^2(\tau) \geq 0.4$) slow events

No.	Number of hours between 12:00, February 2, 1993 and center of time window	Date of event (center of time window 672 hours long)		Nonstationarity measure maximum
1	736	03:00	05.03.93	0.522
2	1745	04:00	16.04.93	1.355
3	12076	15:00	20.06.94	1.483
4	18207	02:00	03.03.95	0.508
5	21819	14:00	31.07.95	0.728
6	25418	13:00	28.12.95	0.694
7	26905	12:00	28.02.96	0.468

Here, $u(t)$ is the incremental series, and $y(t)$ is the filter output subject to further analysis. The parameter b in (15) was defined as the first-order coefficient of autoregression (5), taken with the minus sign and, similar to (9), estimated from the entire sample of the corresponding incremental series $u(t)$. This estimate assures that operation (15) with the “globally” determined factor b has no effect on the recognition of local anomalies with the lifetime comparable to the half-length of the window L. The factor b employed for the series analysis whose results are presented below ranges from 0.720 to 0.849. Thus, operation (15) is an additional, although “incomplete,” differentiation.

The final preliminary operation consists in the suppression of harmonics at periods of more than 50 h (which may be considered as low-frequency harmonics for the given L) using the “soft” Butterworth filter with a slope of 5 [Kanasevich, 1985].

Figure 2 plots the evolution of the nonstationarity measure calculated with the use of double moving time window of half-length $L = 336$ hours for the aggregated signal of all four time series after the application of preliminary operations described above and elimination of the atmospheric pressure effect. These curves differ in the autoregression order q of model (5), running through values of 1, 2, 4, and 8. It is rather difficult to determine which of these values is correct for a given length of the sample L, although there exist formal criteria for the solution of this problem (e.g., the Akaike criterion). These criteria have proven to be a success in the case of model time series, and the experience of their application to the analysis of real data [Kashyap and Rao, 1983; Marple, 1990] shows that the approach based on the trial-and-error fit of q values is most reliable. The plots of Fig. 2 are based just on this approach.

As seen from Fig. 2, main characteristic features of function (13) are stable with respect to the q parameter within its variation range from 1 to 8. The autoregression order $q = 8$ appears to be rather adequate because, on the one hand, it is sufficiently robust with respect to the influence of statistical fluctuations of estimation and, on the other hand, this value is sufficiently high for a sample of 336 samples, in order to attain reasonable sensitivity to variations in signal properties. Comparative stability of the estimates demonstrated in Fig. 2 implies that the optimum value of q may be even greater than 8. However, in order to obtain stable results, possible values of q are intentionally bounded from above, and the value $q = 8$ will be used in what follows. Thus, we will ignore weak events that might be recognized at a greater order of autoregression.

Another problem is the choice of the significance level such that statistic (13) exceeding this level is considered as evidence of an event. We used a level of 0.4 chosen as a value which allows reliable identification of anomalies that are purely visually appreciated as significant (Fig. 2d). In order to statistically substantiate this value, a series of Gaussian white noise as large as 150000 samples was generated and processed by the algorithm with $q = 8$. The resulting maximum of statistic (13) was equal to 0.246, i.e., the chosen level is nearly twice as high as the maximum estimate of purely stochastic fluctuations in the value (13), in the case when the algorithm is applied to a signal *a priori* free of any events. Therefore, the chosen level is statistically significant.

As seen from Fig. 2d, the structure of nonstationarity measure peaks is often rather complicated and represents a group of closely spaced maximums. Although each group may include several peaks exceeding the significance level, a reasonable approach is to choose only one, maximum peak and consider it as the center of a $2L$-long time interval most involved in the related slow event. Seven such groups with a maximum peak exceeding a 0.4 level are characterized in the table.

We emphasize once more that the anomalies listed in the table were recognized due to the higher resolution attained through the aggregation of a collective component to all of the series analyzed. The amplitude of this component is very small compared to local noise, so that a separate examination of each series is by no means capable of recognizing such an anomaly against noisy background. Figure 3 shows the plots of function (13) based on the estimation procedure of nonstationarity measure evolution applied to the initial series for the same parameters as in Fig. 2d, after the

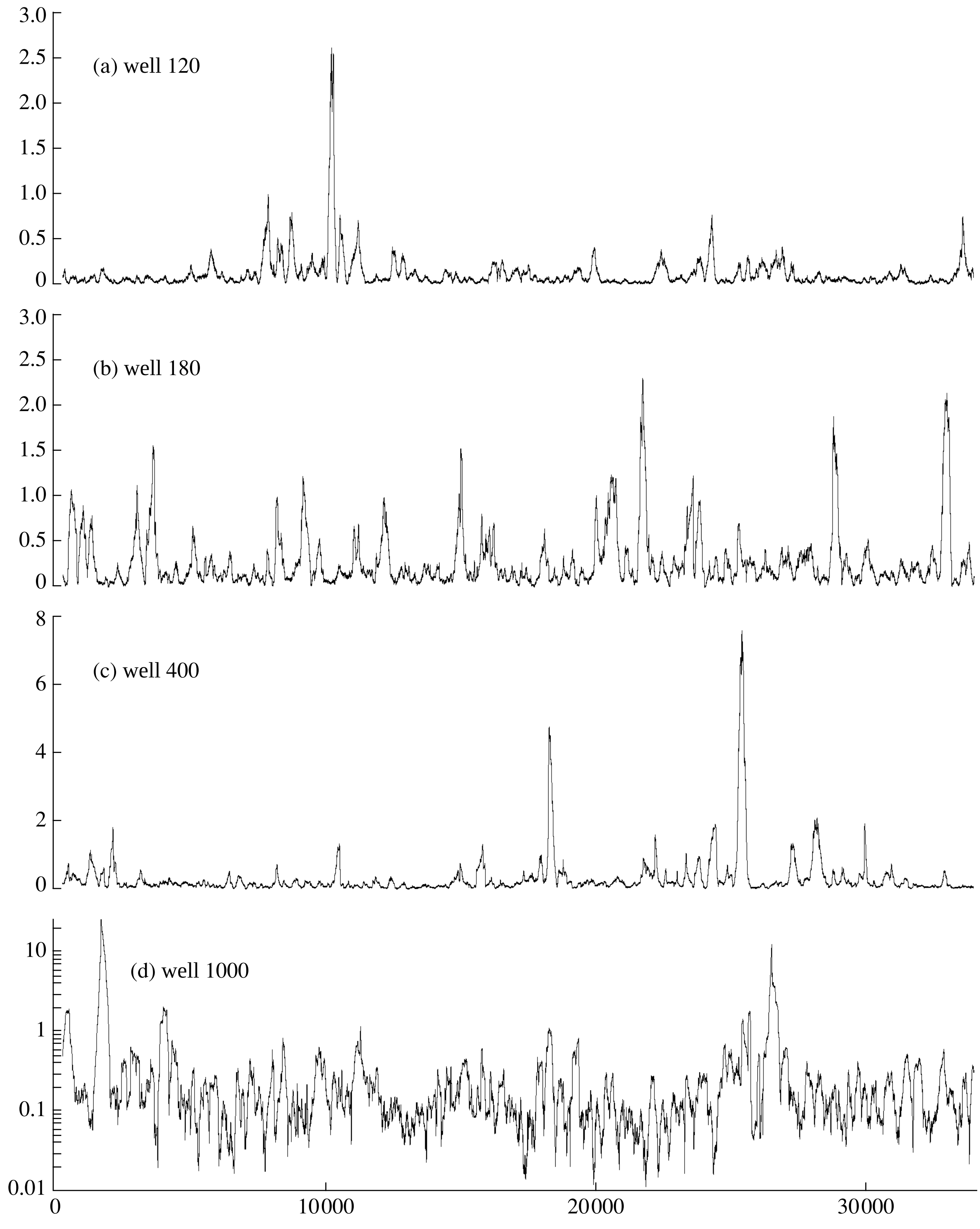

Fig. 3. Nonstationarity measure variations in the initial time series of groundwater levels, estimated with the use of a double moving time window 672 h (28 days) long after elimination of the atmospheric pressure effect. The autoregression order is $q = 8$; τ is the time interval between the moment 12:00, February 2, 1993 and the center of the window.

removal of the atmospheric pressure effect and application of the same preliminary operations as in Fig. 2d. The range of variations in the nonstationarity measure is seen to be considerably wider as compared to Fig. 2, so that data from well 1000 required the logarithmic scale in order to visually distinguish smaller variations against the two most intense peaks of statistic (13). As is evident from Fig. 3, the evolution of measure (13) along each separate series has little in common with Fig. 2, which is explained by a small amplitude of the collective component as compared with local noise.

CONCLUSION

A method is offered for recognition of anomalies, based on data from low-frequency sensors of a geophysical monitoring system; the anomalies appear as nonstationarity features in the collective behavior of a higher frequency component in the processes recorded. By analogy with slow earthquakes, we proposed to call these anomalies "slow events." The latter may arise due to activation of energy dissipation processes in the upper crust, intensifying creep motions at boundaries between blocks. Seven slow events were identified from the case study of a four-dimensional time series representing variations in the groundwater level, recorded in different aquifers of the Moscow region during the period from 1993 through 1996.

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