Nonlinear Science issues in the dynamics of unstable rock slopes: new tools for rock fall risk assessment and early warnings

JIŘÍ ZVELEBIL[1], MILAN PALUŠ[2] & DAGMAR NOVOTNÁ[3]

[1]*Geo-tools NGO, U Mlejnku 128, 250, 66 Zdiby & Czech Geological Survey, Klárov 3, 118 21 Prague 1, Czech Republic (e-mail: zvelebilj@seznam.cz)*

[2]*Institute of Computer Science, Academy of Sciences of the Czech Republic, Pod vodárenskou věží 2, 182 07 Prague 8, Czech Republic*

[3]*Institute of Atmospheric Physics, Academy of Sciences of the Czech Republic, Boční II/1401, 141 31 Prague 4, Czech Republic*

Abstract: Time series of displacement data from unstable rock slopes contain 'hidden' information about the dynamics of slope failure. This information cannot be found when using the current linearly causal paradigm based on analytical methods, but is revealed when numerical and graphical methods from the toolbox of the Nonlinear Sciences are applied. The occurrence of fractal patterns, which suggests a qualitative difference between intrinsic slope movement dynamics of time series from the near-to-equilibrium and the far-from-equilibrium dynamical states of slope failure systems, is an example of such a 'hidden', diagnostically important indicator. It helps to identify the stage of immediate danger of rock fall occurrence, just in time to launch an efficient early warning. Phase portrait and correlograms of time series proved to be suitable for earlier revelation of transitions from the near-to-equilibrium to the far-from-equilibrium dynamical states, as well as for helping to distinguish between intrinsic slope movement dynamics and climatically driven reversible deformation activity.

The holistic paradigm of the nonlinear complex character of natural systems is gaining credit in various fields of geoscience (e.g. Turcotte 1997, 2000; Phillips 1999; Viles 2001; Sivakumar 2004). Natural geosystems are in fact very complex and highly interactive; their parts interplay with each other, forming 'a network of networks', with the possibility of surprising new qualities emerging in their behaviour or attributes. These qualities could not be deduced simply from the quality of the interacting parts, because the whole geosystem is more than just a sum of its parts. In addition, findings about such systems are contextually dependent. They can be fixed in being causal or random at the same time, according to the specific relationships that are studied within them, or because of the relationship chosen according to the spatial-temporal scale used.

The problems that arise when we try to understand these very complex systems using linearly analytical tools of 'classical' physics are well known, as discussed in nearly every book dealing with nonlinear dynamics and dynamical systems (e.g. Cohen & Stewart 1995; Bar-Yam 1997; Kantz & Schreiber 1997; Meakin 1998). Here, we would like to stress that current 'classical' methods fail not only in their 'holy aim' to be able, if initial conditions within the system are known, to predict future behaviour precisely, but sometimes also in an adequately realistic description of the actual state of the given geosystem.

This situation was recognized in the early stages of research in rock slope failure (cf. Terzaghi 1962; Müller 1980). Since then, two different approaches have been developing side by side in the field of engineering geology. The first one, known as a 'classical' geomechanically based approach, aims at elaborating complex models that take into account more and more factors and processes (e.g. Poisel & Preh 2004; Poisel & Roth 2004).

The other approach is instead based on a holistic model of dynamics of unstable slope (i.e. on the description of the behaviour of that slope). The quest for such a model was started by Bjerrum & Jorstadt (1968) in their famous paper about rock falls and their forecasting in Norway. They called their approach the 'Observational Method', because it was based on assessment of slope monitoring results. To fix an actual degree of rock slope instability, the authors recommended a scaled list of symptoms, characteristic dynamical patterns of displacement and deformation phenomena, whose scaling would correspond with the different stages of preparation of catastrophic slope collapse.

Since then, such 'empirical–phenomenological models' of temporal development of slope

From: CELLO, G. & MALAMUD, B. D. (eds) 2006. *Fractal Analysis for Natural Hazards*. Geological Society, London, Special Publications, **261**, 79–93.
0305-8719/06/$15.00 © The Geological Society of London 2006.

movement activity have been used to assess instant slope instability and temporal prognostication of rock fall occurrence (Saito 1969; Voight & Kennedy 1979; Fuzukono 1984; Zvelebil 1985, 2004; Rochet 1992; Zvelebil & Moser 2001). Those models were applied mainly to interpret the geometric features of data curves in common, time-deformation, Cartesian plots of monitoring time series. Limitations of those empirical–phenomenological models have, however, been questioned since they first came into use (e.g. Zvelebil 1996; Moser *et al.* 2002; Moser 2003).

Nonlinear analysis and modelling of time series data offer an opportunity to overcome those limitations. More than 16 years ago, Zvelebil (1984) started to compare the complex hierarchical patterns of time series from dilatometric (thermal expansion/dilation) monitoring of rock cracks, according to the concepts and methods of self-organizing systems such as those discussed in Nicholis & Prigogine (1977) and Prigogine & Stengers (1984). He arrived at the conclusion that 'Part of the important information which is embedded in monitoring time series, is hidden. When current linear-based methods are employed it mimics itself as a seemingly random noise (e.g. Růžek & Zvelebil 1993). Hence, we should look for new more appropriate methods, and the toolbox of nonlinear dynamics seems to be a reasonable choice' (Zvelebil 1996).

The present paper deals with the preliminary results of a joint challenge for an engineering geologist, a mathematician, and a physicist to find new, mathematically rigorous tools for better handling of monitoring data from unstable rock slopes.

Search for hidden information

In this paper, the term 'nonlinearity *sensu stricto* (s.s.)' is defined, in a mathematical sense, as dynamics that cannot be reduced to a standard linear autoregressive model or its static, possibly nonlinear transformation. A special example of such processes can be deterministic chaos. 'Nonlinearity *sensu lato* (s.l.)' implies a wider, hence vague meaning; it has been introduced in the field of Nonlinear Science to provide a summarizing label for the very specific behaviour features of complex systems that are difficult to elucidate within the ordinary frame of linear paradigms (i.e. nonlinearity s.s., emergency, self-affinity, self-organization, self-organized criticality, etc.) (e.g. Bar-Yam 1997).

In our search for hidden information, we used data from a regional monitoring network of sandstone rock slopes in northwestern Bohemia (e.g. Zvelebil 1989, 1995; Zvelebil & Park 2001). The network started operating in 1979 in order to monitor the Czech–German traffic corridor through the deep canyon of the River Labe. It has been gradually expanded to encompass slopes above settlements and tourist paths in areas of the highest rock fall risks within the National Park Bohemian Switzerland. From the wide spectrum of methods available for measuring rock slope deformations, dilatometry was chosen. Using that method, systematic measurements of changes in length (displacements) of measuring lines placed across rock cracks, have been carried out.

Nowadays, the network spreads over 327 rock volumes with more than 900 sites where dilatometric measurements of relative displacements along rock cracks are currently measured (cf. Vařilová & Zvelebil 2005). The longest monitoring time series span over 25 years. The data set includes nearly all the developmental stages of sandstone rock slope instability. The quality of time series differs according to the monitoring techniques; these include manual measurements, carried out with a portable rod dilatometer, which cover the longest time interval and the broadest spectrum of developmental stages occurring in the course of a rock fall preparation. Unfortunately, the quality of the data suffers from irregular sampling and from variations in the sampling time interval, which ranges from a few days to one month. This irregular sampling forced us to modify well-established methods of Nonlinear Dynamics (e.g. Kantz & Schreiber 1997), or to re-sample the data in order to perform the analysis. The series used for the analysis included some 480 to 612 samples and the available time span was from January 1984 to June 2001. Besides the time series obtained from manual dilatometry, we also analysed the results supplied by automatic acquisition systems. They include from 13,000 to 123,000 samples taken at regular frequencies of 5 or 10 minutes. Those time series spanned from 3 to 14 months.

Slope monitoring signals consist, as do all signals from natural dynamical systems (e.g. Perry *et al.* 2000), of a mixture of coexisting and interacting dynamics. For this reason, signals relating to rock mass failure have to be distinguished from displacements and deformations of different origin. There is quite a long list of displacements/deformations due to causes other than slope movements resulting from rock mass failure (cf. Zvelebil 1989); it includes mainly data due to reversible responses of the rock mass to perturbations by the external environment. The most important one is represented by changes of rock-block volumes due to temperature variations. The patterns of these thermal dilations of rock blocks correspond to the hierarchically structured system of climatic cycles, from the diurnal and seasonal up to ones taking many years (Zvelebil 1995). The whole polygenetic assemblage of those reversible responses to perturbations by the external environment will be called the 'standard activity' (SA) in the following sections.

In order to minimize errors in distinguishing between signals due to SA manifestations and those peculiar to rock slope displacement, all data without any detectable evidence of slope movement activity were omitted from the analysis, and the remaining time series were divided into two groups: one representing the 'near-to-equilibrium' signals and the other representing the 'far-from-equilibrium' states of unstable slope systems. The 'near-to-equilibrium' (NTE) series were recorded on slopes that exhibit irreversible long-lasting slope movements, but where no patterns indicating rapid slope collapse were identified (e.g. Figs 1a, 5a–c). The 'far-from-equilibrium' (FFE) series were obtained from recently collapsed slopes only (Figs 2a, 3a, 4a, 5d, e).

Graphical tools: phase space portrait and correlogram

A major achievement of Dynamical Systems Theory has been that of bringing us back to geometry as an important and rigorous tool for studying system dynamics (Abraham & Shaw 1992). The geometrical patterns of common displacement–time plots have played a prominent role in data interpretation using current empirical–phenomenological models (Voight & Kennedy 1979; Fukuzono 1985; Zvelebil 1985, 1996; Zvelebil & Moser 2001). These types of plots of rock slope displacements are represented by Figures 1a, 2a, 3a, 4a, and 5a. In this paper, two other ways to analyse time series, *phase portraits* and *correlograms*, were tested. Although these are quite common tools in Dynamical Systems and *Harmonical* analysis, they have not yet been used in the field of slope monitoring.

Phase portraits of 'raw', that is, non-filtered monitoring time series embedded in two- and three-dimensional phase space, have been found to be quite appropriate in fulfilling the crucial task of detecting the transition from NTE to FFE dynamics. A phase space is a vector space, in which any point specifies the instant state of the given system and vice versa. It is a powerful tool for giving a geometrically synoptic display of characteristic patterns of very complex behaviour that, as for non-deterministic systems, can be displayed by a huge (possible infinitive) set of states and some kinds of transition rules that specify how the system may proceed from one state to the other (Kantz & Schreiber 1997, pp. 30–31). As the behaviour of the system develops in time, a sequence of its state points clusters into a geometrical entity of *state trajectory within phase space*. Any geometrically regular pattern that emerges by clustering of *system state trajectories* in phase space corresponds to certain regularities in behaviour of the given system.

Geometrical patterns of the NTE state are shown in Figure 1 and the FFE ones in Figure 2. The phase portraits are more synoptic than the current displacement–time plots of the series in question, especially when very long time series are being studied. In the phase portrait, all regular patterns which should otherwise be laboriously traced along the whole length of such time series, are 'compressed' in one section of phase space, making an *attractor image*, that is, a distinct geometrical pattern that represents the whole group of similar but not necessarily equal types of behaviour of the given system. Any transition from the given set of patterns of behaviour to some other type of behaviour corresponds to the system state trajectory that is, usually quite distinctly, heading out of the *basin of a given attractor* (compare Fig. 1b with Fig. 2b).

In Figure 2b, the heading-out trajectory was interpreted as an indication of a phase shift from the current NTE state (marked β_1, near the origin in Fig. 2b) to an FFE type of system behaviour (marked α). It was possible to detect this NTE–FFE shift even 13 months before (Fig. 2a). The inverse development is marked β_2 in Figure 2b. In Figures 3a and b, there is another representation of the FFE to NTE shift, which occurred in the course of new local crushing at the toe of a high rock wall. After an initial, high activity of new joint spreading, a stress rearrangement towards an inner less-disturbed zone occurred, resulting in a gradual low-down of the displacement along the new joint.

Correlograms of the time series can help us to identify where displacement patterns from different parts of the slope display interrelated features, that is, which series are produced or influenced by the same process. In this paper, the variant called XY plot in MATLAB usage is adopted. Data from different time series or of the same type (but from different places) or of different types (e.g. displacement and temperature) from the same place, are plotted in two 2D or 3D plots. Any relationship between those time series is characterized by a specific pattern, which may be quantified by measuring coupling and synchronization (Paluš *et al*. 2001; Paluš & Stefanovska 2003; Pikovsky *et al.* 2003).

In Figures 4a–b, we show data from different parts of a large, unstable rock pillar. The high degree of synchronization of movement events can be spotted between records from the uppermost scarp and the lower frontal and toe parts of the pillar (Fig. 4b). The results of the analyses shown in Figure 4 support our preliminary assumption about the existence of deep-seated phenomena affecting the whole rock mass.

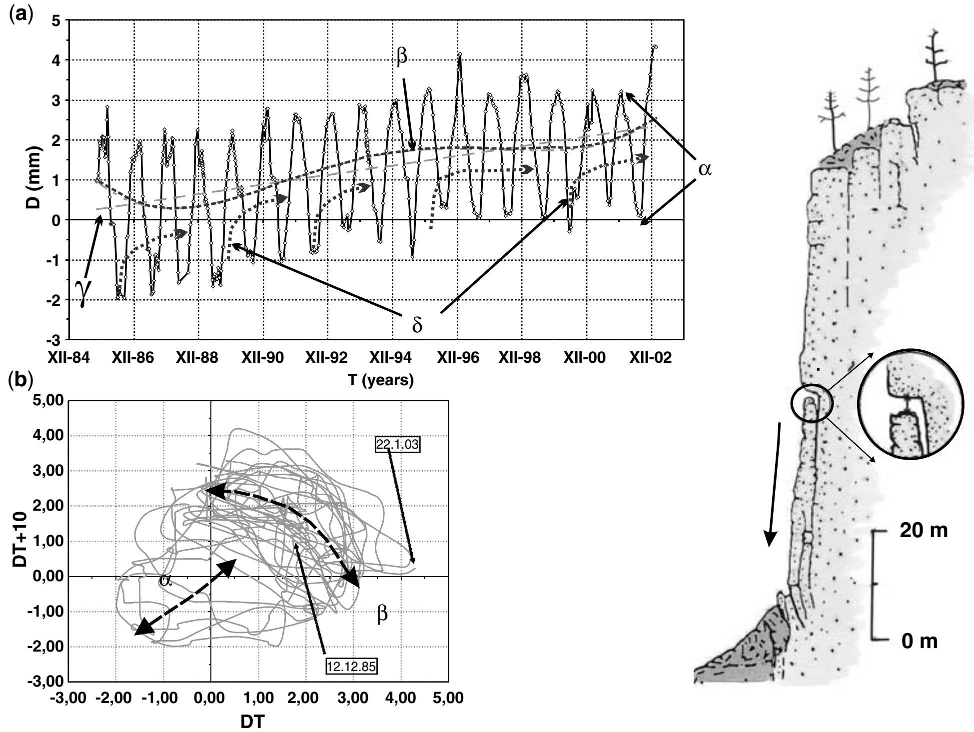

Fig. 1. (**a**) Regular and (**b**) phase space portrait plots of the same time series representing the medium stage of preparation of a rock fall, that is, the 'near-to-stability' (NTS) state of the system. The data refer to a twenty-year record of a slowly sinking and toppling rock block with a volume of 1600 m^3, which forms the toe of a 100 m high rock wall. It may be observed that it is sometimes difficult to assess the intrinsic dynamics of relative displacements between rock blocks by slope stability failure using time–displacement data, as the patterns of Figure 1a are distorted by some underlying 'noise' (here named 'standard activity', SA). SA may be a result of (α) seasonal activity with amplitude of about 3 mm, generated by volume changes of rock blocks as a result of temperature variations, and to (β) an almost cyclic activity, with a duration of 10–11 years; this type of SA may also be of climatic origin. The intrinsic dynamics of slope stability failure (γ) show instead a long-lasting linear trend with a gradient of 0.1 mm/year. Other types of displacements of dubious origin (δ) include a 3–5 year cycle, which may be simulated by a simple vector addition of a 10–11 year almost cyclic SA with linearly increasing irreversible displacement, or may be at least partially caused by changing the rate of irreversible slope movements. A two-dimensional phase space portrait of the same regularly resampled data set is shown in (**b**). It may be seen that the resulting pattern mimics a hypothetical attractor. Six loops of state trajectories shifted by translation gliding (α) along the symmetry axis of the attractor correspond to the periods of increased activity of irreversible movements, and all denser areas (β) correspond to periods of relative calm.

Numerical tools: distributions and temporal correlations

Full details of mathematical scrutinizing of given monitoring time series are presented in Paluš *et al.* (2004). Here, we summarize our main results. For this type of analysis, the basic division into two groups (the NTE and FFE groups) was retained; however, the majority of time series had to be excluded from the analysis because they were incomplete (gaps too large in the records). Only four FFE and five NTE series were suitable for analysis (see Fig. 5 and Figs 1a and 2a). The chosen time series were also regularly resampled upto 1024 samples. Because the raw dynamics of the series was clearly dominated by atmospheric influences, mainly by temperature (visible demonstrations of SA), the atmospheric variables were also considered in our analyses. With this aim, meteorological data were resampled.

Our numerical tools include techniques of uni- and multivariate surrogate data with simple phase randomization, fast Fourier transform and the Schmitz & Schreiber (1999) construction method, and the method of information–theoretic functionals–redundancies of Paluš (1995*a*, *b*). The

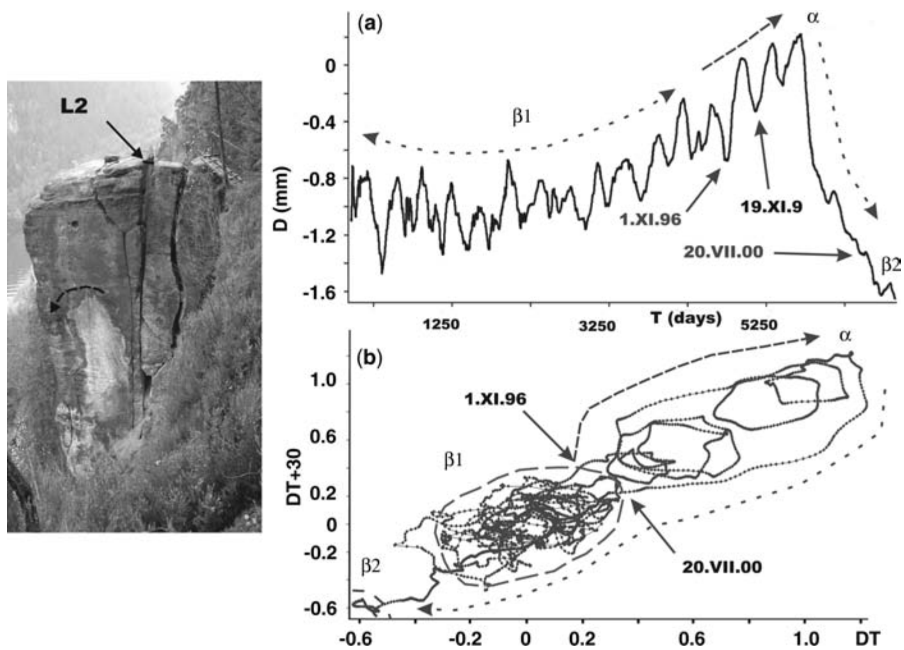

Fig. 2. (**a**) Time–displacement plot and (**b**) phase portrait of time series from site L2 show the transition from (α) near-to-stability (NTS) to (β) far-from-stability (FFE) states of a slope system. The time–displacement plot (**a**) enabled us to empirically detect markers of the NTE–FFE transition from November 1997, whereas the 2D phase portrait diagram (**b**) allowed us to detect this same information one year earlier, when a state trajectory heading out of the NTE attractor was clearly defined.

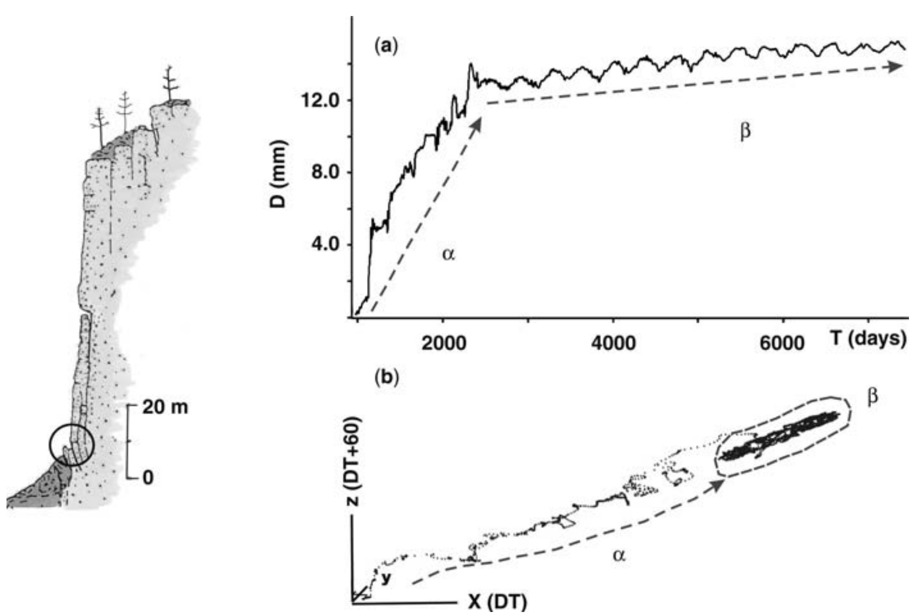

Fig. 3. (**a**) Time–displacement plot and (**b**) 3D phase space portrait of the FFE (α) to the NTE (β) transition in the rock slab of Figure 1. From the phase portrait diagram, one may see that there is a general shift of the system state trajectory towards the NTE attractor, before it finally sets inside the β space.

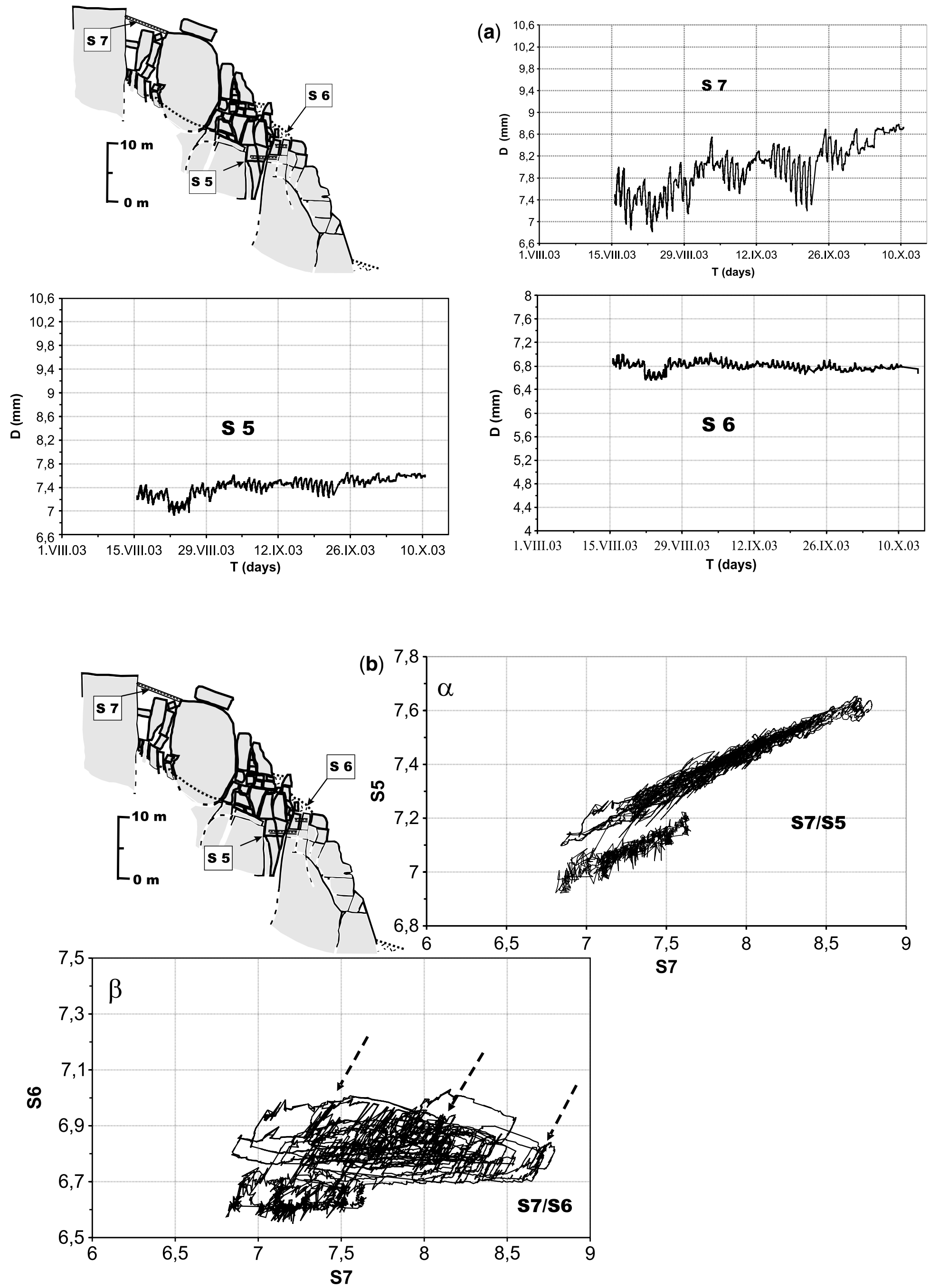

Fig. 4. (**a**) Displacement patterns of time series from three different positions (S5, S6, S7) within a rock pillar with a volume of 3000 m^3. (**b**) Correlograms of the same data set. The high degree of synchronization (α) between data from the uppermost section of the pillar (S7) and those from the lowermost section (S5) suggests that slope movements are induced by deep-reaching processes. The lack of synchronization (β) between data from section (S7) and (S6) was instead interpreted as resulting from an independent process occurring near the surface and affecting smaller rock volumes. Minor synchronization events (marked by the arrows in β) have been related to the rock mass response to climatic perturbations.

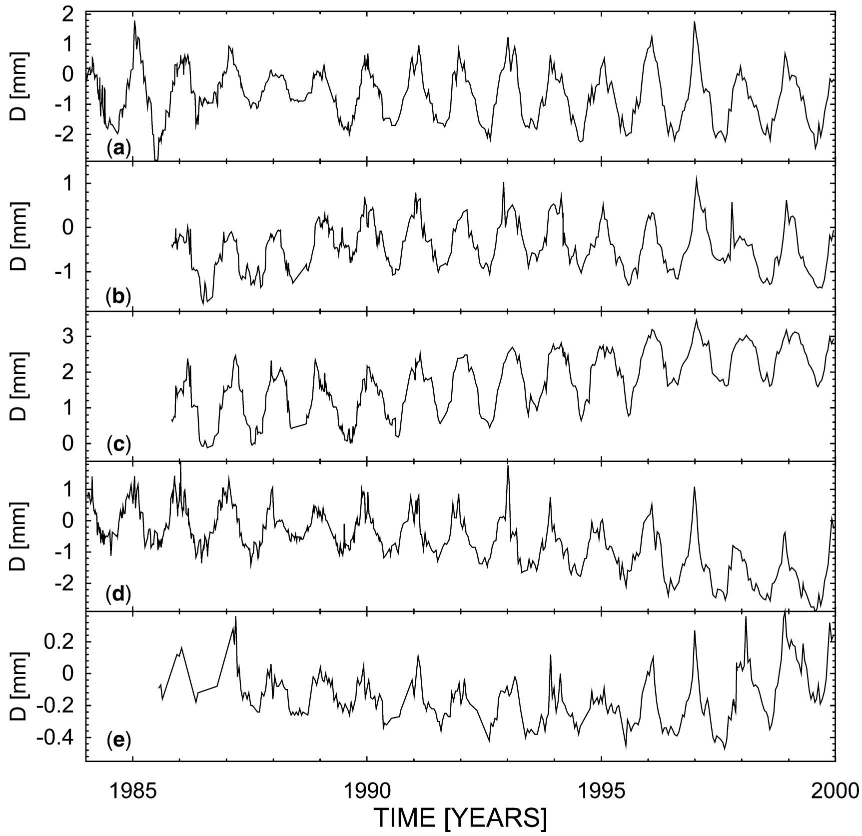

Fig. 5. Dilatometric measurements of relative displacements observed across cracks in sandstones: NTE dynamics (**a**–**c**), FFE dynamics (**d**, **e**).

intrinsic slope dynamics of both the NTE and FFE time series were characterized using analyses of the residuals (Fig. 6) obtained from the dilatometric series after removing meteorological influences. Those residuals were obtained by triple linear regressions (DATAPLORE SW Package, 2006). The plots of empirical probability for amplitudes larger than the given value were constructed for the distribution tests. In order to study the dynamics and temporal correlations, the power spectra of residuals were calculated (DATAPLORE SW Package, 2006). Scaling of the distribution of fluctuations and of the distribution of energy over the power spectrum, as well as a possible scaling of fluctuations in their temporal evolution were studied using a detrended fluctuation analysis (Peng *et al.* 1994, 1995; Goldberger *et al.* 2000). Using the listed tools, the following results were obtained.

(1) *Nonlinear dynamics s.s.* The necessary conditions for proving the presence of nonlinear dynamics s.s. were not fulfilled (Figs 7–10). Our finding predominantly concerned the strong influence of atmospheric variability and seasonality on monitoring the time series, as these were mainly expressed by their SA component. The influence proved to be linear, but, at the same time, not trivial. Note that two previously unknown time lags of 100 and 123 days were found from regressions of the annual cycle of atmospheric temperature dynamical features onto the dilatometric series.

(2) *Nonlinearity s.l.* This was detected in the intrinsic slope dynamics of the FFE series, but not for the NTE ones. There is a qualitative difference of correlation decay in the dynamics of the NTE and FFE series. The residuals from the NTE series possess non-trivial, but nevertheless linear dynamical features. They are non-Gaussian, asymmetrically distributed, fat-tailed (e.g. Malamud 2004; Malamud & Turcotte 2000) fluctuations with short-range correlations (Fig. 11a).

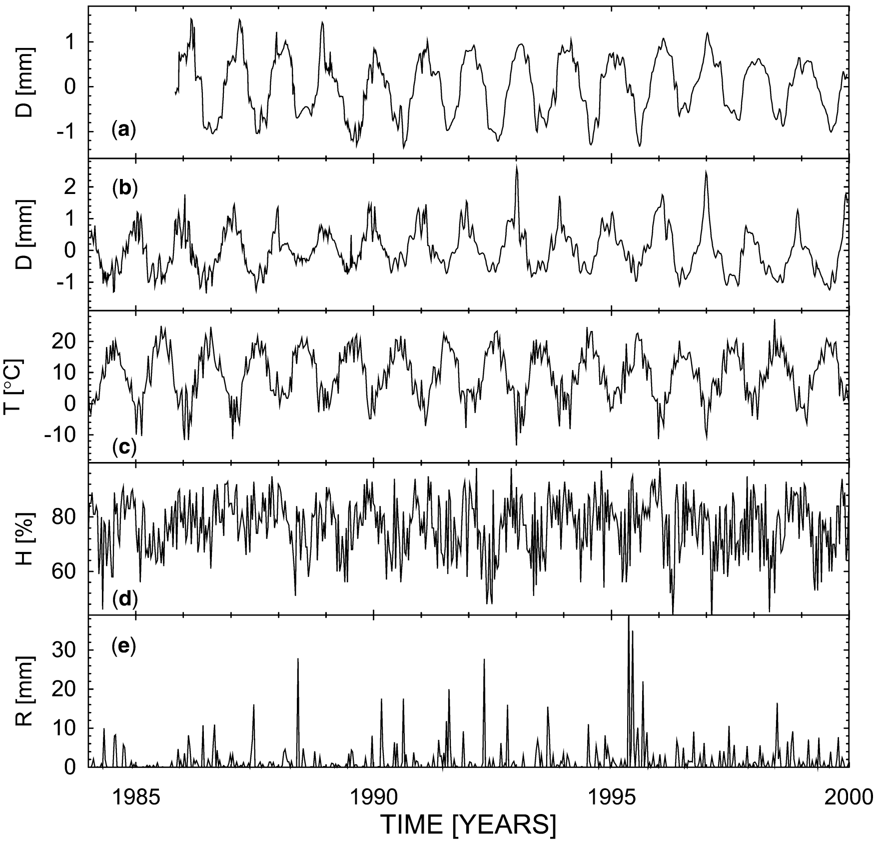

Fig. 6. Linearly detrended NTE (**a**) and FFE (**b**) time series of dilatometric measurements D, and time series relative to (**c**) atmospheric temperature T, (**d**) humidity H, and (**e**) precipitation R.

Nonlinearity s.l. could be considered for the FFE residuals. They are characterized by an asymptotic power-law distribution on the 'fatter' side of their non-Gaussian distribution (Figs 11b and 12). Its decay coefficients range between 4 and 5, that is, outside the range of stable Lévy distribution $0 < \mu < 2$ (Schertzer & Lovejoy 1991). For this type of fluctuation, the dynamics is intermittent and high-order moments diverge. Furthermore, the dynamics of FFE residuals possesses persistent long-range correlation of self-affine processes (an occurrence of $1/f$, that is, of pink noise, see Turcotte 1989; Barrow 1995; Malamud & Turcotte 1999). Moreover, two scaling regions were consistently identified by both the spectral and the detrended fluctuation analyses. In time-scales between 4 and 11 weeks, the persistence is characterized by the spectral decay coefficient $\beta \approx 2$, which corresponds to a Brownian motion. Time-scales from 11 weeks to almost 2 years are described by the spectral decay coefficient $\beta \approx 1.5$, which corresponds to a fractional Brownian motion.

The information obtained by using this nonlinear approach for the study of unstable rock masses also poses new questions; some of them are discussed in the following sections.

Discussion

Specific results

There is a disproportion of spatial-temporal scales between monitoring records and the development of slope failure. The relatively short NTE time series represent merely point-like samples of the precritical stages of slope failure systems, whereas the FFE time series roughly match the critical precollapse stage. Unfortunately, in our case study, sampling of FFE time series was too coarse to reveal the finer details of their dynamics. Hence, our information is relevant only for dynamical

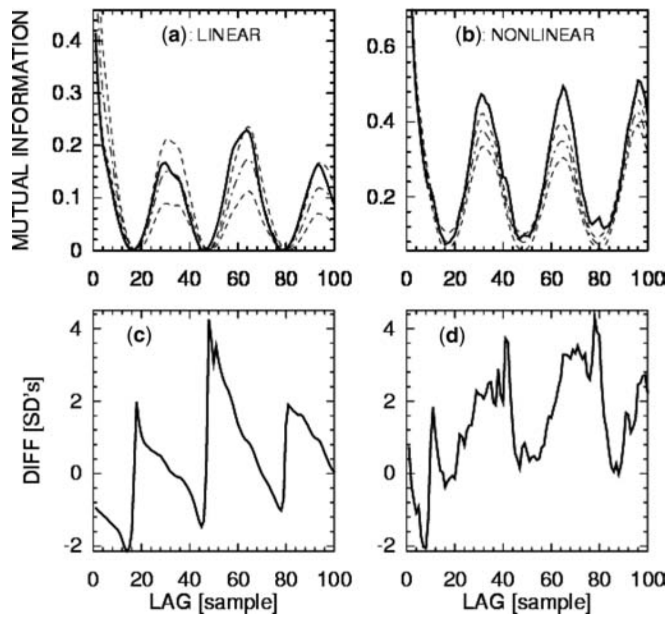

Fig. 7. Nonlinearity test of a detrended unstable dilatometric time series, using (**b**, **d**) mutual information I ($X(t)$; $X(t+\tau)$), and the check of the surrogate data using (**a**, **c**) linear mutual information L ($X(t)$; $Y(t+\tau)$). The values of mutual information (**a**, **b**) from tested data (solid line), mean (dashed-and-dotted line) and mean $\pm$ s.d. (dashed lines) of a set of 30 measurements are shown, as are the statistical differences in the number of standard deviations (s.d.) of the surrogates (**c**, **d**).

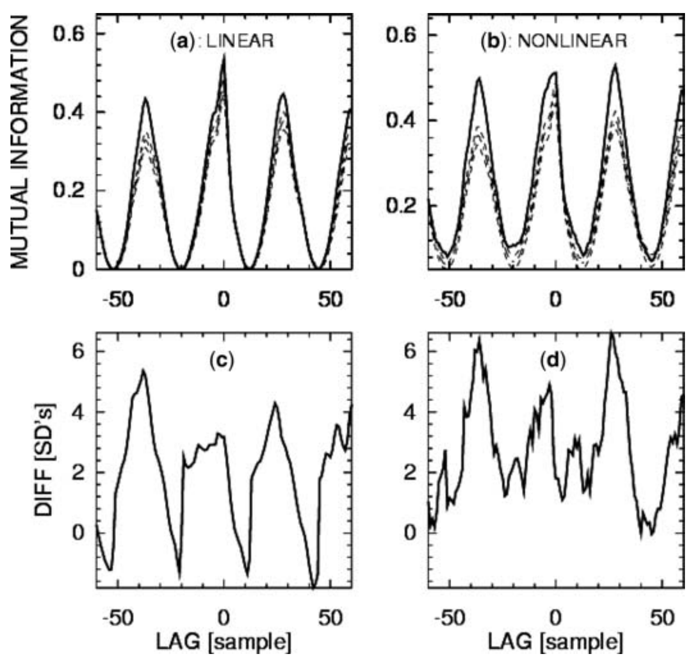

Fig. 8. Testing nonlinearity in the relationship between atmospheric temperature and the detrended unstable dilatometric time series using (**b**, **d**) mutual information I ($X(t)$; $Y(t+\tau)$), and the check of the surrogate data using (**a**, **c**) linear mutual information L ($X(t)$; $Y(t+\tau)$). See caption of Figure 7 for key.

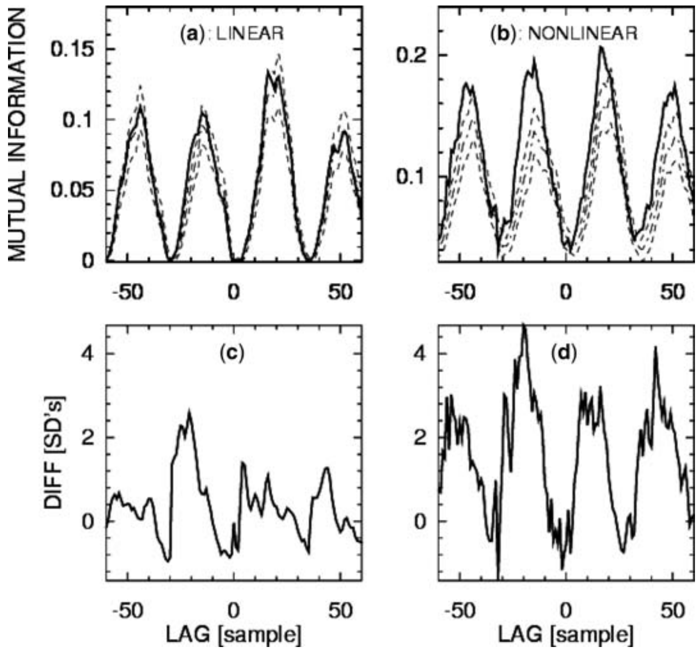

Fig. 9. Testing nonlinearity in the relationship between atmospheric temperature and the residuals of the multilinear regression of the detrended FFE dilatometric time series on the meteorological variables using (**b**, **d**) mutual information I $(X(t); Y(t+\tau))$, and the check of the surrogate data, using (**a**, **c**) linear mutual information L $(X(t); Y(t+\tau))$. See caption of Figure 7 for key.

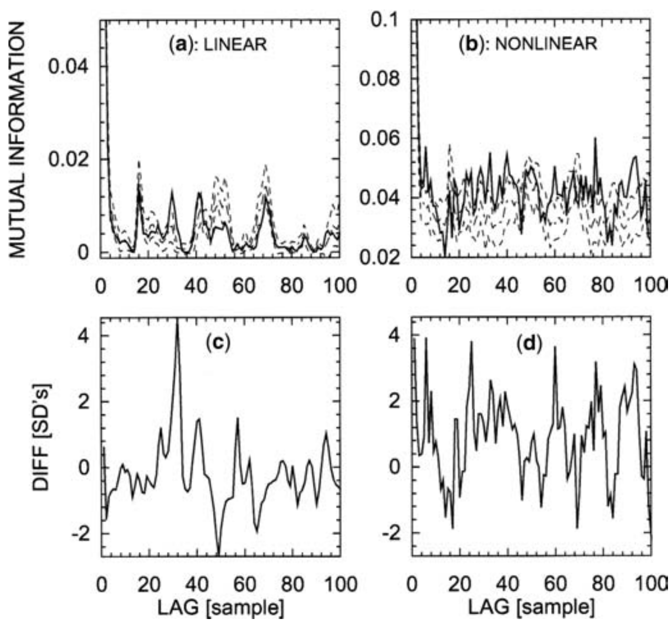

Fig. 10. Testing nonlinearity in residuals of the triple linear regression of the detrended FFE dilatometric time series on the meteorological variables, using (**b**, **d**) mutual information I $(X(t); Y(t+\tau))$, and the check of the surrogate data using (**a**, **c**) linear mutual information L $(X(t); Y(t+\tau))$. See caption of Figure 7 for key.

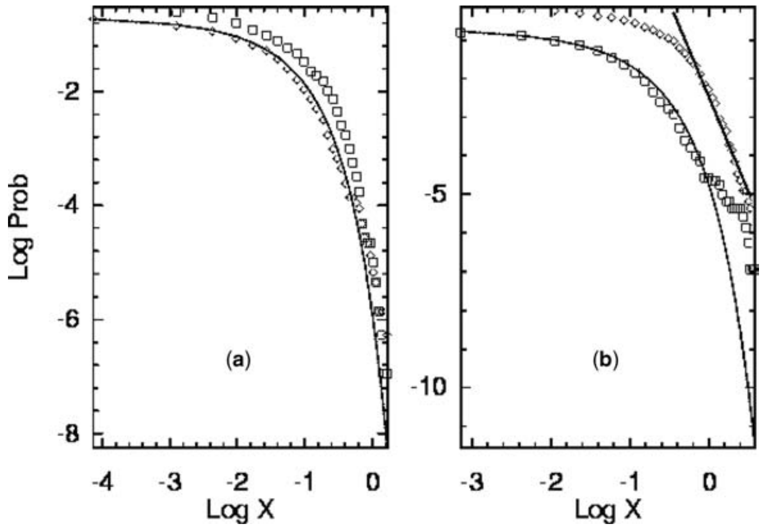

Fig. 11. The empirical probability $P(|x| > X)$ to observe amplitudes larger than a given value X (where x is a deviation from the mean value) for the triple regression residuals of an example of (**a**) NTE and (**b**) FFE time series of dilatometric measurements. Diamonds and squares illustrate left and right sides of the distribution, respectively. The solid line shows the average distribution of 10^5 of a 1024-sample time series randomly drawn from the Gaussian distribution with the same mean and variance as the residual under study.

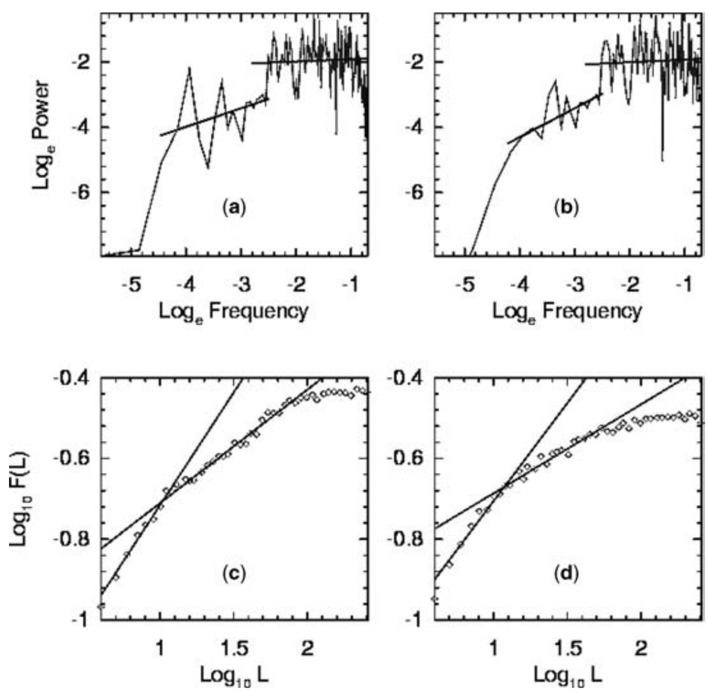

Fig. 12. (**a**, **b**) Power spectra and (**c**, **d**) results of the detrended fluctuation analysis for the differentiated residuals of the (**a**, **c**) single and (**b**, **d**) triple regression of the linearly detrended FFE time series of dilatometric measurements. Thin curves in (**a**, **b**) and points in (**c**, **d**) are the results of the respective methods; thick solid lines in all figures are fitted robust linear regressions in particular scaling regions.

patterns that are sufficiently robust to be fixed by a 14-day frequency sampling condition. On the other hand, these patterns reoccur so frequently that they may be spotted, at sufficient significance levels, within a time interval of about 15 years.

Our results also show that the response patterns of slope failure systems, which represent a family of complex highly interactive catastrophic events, met our theoretically based expectations, as they allowed us to unravel previously hidden information, such as a time lag response of 100 and 123 days. On the other hand, the linear (even though nontrivial) nature of dilatometric time series modulation by climatic influence is rather surprising. In fact, it does not conform to the findings of other authors (e.g. Tausch *et al.* 1993; Kupfer & Cairns 1996; Phillips 1999), as climatic driving, or driving containing any climatic and therefore inherently chaotic component, implies the high possibility of unstable, chaotic elements in the dynamics of the system.

In any case, the relatively simple linear form of climatic modulation does not *a priori* imply any theoretical restriction to improving the ability and reliability of filtering out the SA component from the monitoring signal. The question of whether the intrinsic NTE dynamics really possesses climatic driving or is a consequence of insufficient filtering of the SA component has still remained unanswered. Comparison of the dynamics of NTE time series with records from stable slopes where only the SA component is present should help answer this question.

The reliability of fixed patterns to correspond with intrinsic slope failure dynamics is relatively greater for FFE series. In this case, dynamics includes fluctuations with hyperbolic intermittency and scaling spectra and is supposed to occur in response to the action of cascading, energy-transferring processes (e.g. Schertzer & Lovejoy 1991). The robust fitting of the distribution of FFE residuals can indicate the occurrence of a self-organizing process (Bak & Chen 1991; Jensen 1998; Turcotte 2000; Turcotte & Rundle 2002; Sornette *et al.* 2004). The existence of two scaling regions implies that the intrinsic fractal dynamics of FFE is scale-dependent. Therefore, the next step should be a fractal analysis on short time-scales using high-frequency time series from automated data acquisition systems.

In any case, the qualitative difference between the NTE and FFE dynamics, as well as the geometrically distinct transition form NTE to FFE states and the occurrence of fractal patterns of time series residuals after SA filtering, seem to be quite important for further enhancement of the early warning issue. With this aim, these were successfully used for the safety evaluation of monitoring data during emergency remedial works in Hřensko village in 2002 (Zavoral 2002; Vařilová & Zvelebil 2005). The most recent case history of early distinguishing of rock fall danger, and a successful time-prediction of that rock fall occurrence in Kamenice River Gorge (Vařilová & Zvelebil 2005), has shown that correlograms of displacement time series from different monitoring sites, as well as those relating deformation and temperature changes from the same site, may be useful tools for monitoring data assessment. For this reason they are currently being introduced as a regular part of an integrated monitoring system for the whole territory of the Czech–Switzerland National Park. The method of displacement/displacement correlograms was also successfully applied to clear kinematics of slope movements endangering the Spišš Castle, Slovakia (Baškova 2004; Vlčko 2004).

General implications

Sticking to current evaluation tools for monitoring data, which are based on linear reductionist paradigms, may result in biased or incorrect handling of slope dynamics analysis. The list of possible errors and misleading conclusions includes the following:

(1) Overestimation of the proportion of random noise within the signal, accompanied by an inability to see the 'hidden' order. This is our topical case of hidden information masked by white noise.
(2) The linear presumption; it is only the external influence that matters in changes of system dynamics. This disregards the possibility of dynamical changes due to the action of inner mechanisms of slope failure, as well as the existence of various responses, differing in their timing, of the slope system to the same perturbations. This is a cardinal phenomenon to be considered in every triggering-factor study.
(3) The complex nature of slope failure and the variety of local conditions dictate that fully quantitative specifications are practically impossible, and that even location specifications can be exceedingly difficult to obtain (Phillips 1999).

The above discussion suggests that (1) most of the work done for fixing 'critical threshold values' for external influences on catastrophic slope instability events (e.g. Dikau & Schrott 1999; Rybář 1999, 2004; Schmidt & Dikau 2004) is biased by methodical incorrectness; (2) there is a theoretically given limit for adequacy of results from linearly–causally based numerical models of slope deformation behaviour and stability failure, which cannot be overcome by any further refinement (even for the most sophisticated ones, such as FEM and DEM methods). On the other hand, there is also an exponential law stating the minimal amount of data needed for plausible conclusions about time-series patterns in nonlinear analyses. The practical limit to the embedding dimension of time series that can be analysed in practice has been fixed at a value of 4 (e.g. Hunt *et al.* 2003). Therefore, when analysing relatively short time series (as is quite normal in many practical cases) rather dangerous assumptions have to be adopted, either that the dynamics of the variable chosen for that analysis is affected by only a few state variables (e.g. Henttonen & Hanski 2000) or that such a small embedding level allows detection of nonlinearity s.s. even for large-dimensional time series (e.g. Nychka *et al.* 1992).

In any case, applying inadequately modified methods to data of poor quality or insufficient quantity may result in mathematically inconsistent or implausible findings; hence, a multidisciplinary approach is inevitably necessary for elaborating appropriate models in the spatio-temporal domain. A possible way of simulating the process of rock slope collapse preparation as the development of hierarchically structured, complex systems with multifactor control is by using Self Organized Criticality models, which qualitatively differ from the currently used engineering-oriented ones. In this way, quite new pieces of knowledge could be revealed that have not yet been discovered through spatially–temporally limited field observations (see Holland 1998; Bossomaier & Green 2000).

Conclusions

The main conclusions arrived at with this study are listed as follows:

(1) Monitoring time series from unstable rock slopes reveals more information about dynamics of slope failure than we are able to acquire by current analytical methods. The reason for this is that current methods are based on a linearly causal paradigm, and are founded on empirical–phenomenological models, which are unable to be sufficiently assisted by the processing power of computers when dealing with large amounts of data.

(2) In the case history reported here, the hidden information was revealed when methods from a toolbox of the Nonlinear Sciences were applied. Geometrical methods, the phase portrait, and correlogram of time series have proven to possess greater ability to display the features looked for than the current time–displacement plots. In particular, they proved to be more suitable for revealing transitions from near-to-equilibrium (NTE) to far-from-equilibrium (FFE) dynamical states of slope failure system, as well as to help in distinguishing between intrinsic slope movement dynamics and climatically driven SA activity.

(3) The qualitative difference between intrinsic slope movement dynamics of the NTE and FFE time series is important for assessing slope behaviour. The NTE series possess a linear non-Gaussian but asymmetrical fat-tailed distribution of movement events. In contrast, the FFE series are nonlinear (s.l.) features of persistent long-range correlation of self-affine processes with two scaling regions.

(4) The graphical methods and the numerical testing of fractal features seem to be very promising for assessing the state of immediate rock fall danger. To this end, it also suggested that modelling the dynamics of preparation for rock slope collapse as a complex self-organizing system may be appropriate to reveal the crucial dynamical patterns of slope failure systems.

The study was supported by T110190504 Project of the Academy of Sciences of Czech Republic, by MSN 00216 20831 Project of Ministry of Education, Youth and Sports of Czech Republic, and the Institutional Research Plan AV0Z10300504. The authors wish to thank the editors for their valuable comments, stimulating questions, and manuscript corrections, which helped to improve the overall quality of the paper.

References

Abraham, R. H. & Shaw, C. S. 1992. *Dynamics. The Geometry of Behaviour.* Addison-Wesley Publishing Company, Reading, Massachusetts.

Bak, P. & Chen, K. 1991. Self-organized criticality. *Scientific American*, **264**, 46–53.

Bar-Yam, Y. 1997. *Dynamics of Complex Systems.* Addison-Wesley, Reading, Massachusetts.

Barrow, J. D. 1995. *The Artful Universe.* Oxford University Press, Oxford.

Bašková, L. 2004. Analysis of bedrock dynamics and its influence on stability of historical buildings (in Slovak). PhD Thesis, Komenius University, Bratislava.

Bjerrum, L. & Jorstad, F. 1968. Stability of rock slopes in Norway. *Norges Geotekniska Institutt Publikasion*, **79**, 1–11.

Bossomaier, T. R. J. & Green, D. G. 2000. *Complex Systems.* Cambridge University Press, Cambridge.

Cohen, J. & Stewart, I. 1995. *The Collapse of Chaos. Discovering Simplicity in a Complex World.* Penguin Books, Harmondsworth.

DATAPLORE Software Package. 2006. Software used for resampling, detrending, filtering, linear regressions, and spectral analyses. World Wide Web Address: http://www.ixellence.com/en/products/dataplore_index.html [Accessed 1 July 2006].

DIKAU, R. & SCHROTT, L. 1999. The temporal stability and activity of landslides in Europe with respect to climatic change (TESLEC): main objectives and results. *Geomorphology*, **30**, 1–12.

FUKUZONO, T. 1985. A new method for predicting the failure time of a slope. *In*: *Proceedings of the 4th International Conference and Field Workshop on Landslides*, Tokyo, Tokyo University Press, 145–150.

GOLDBERGER, A. L., AMARAL, L. A. N. *ET AL*. 2000. PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. *Circulation*, **101**, e215–e220. World Wide Web Address: http://circ.ahajournals.org/cgi/content/full/101/23/e215 [Accessed 1 July 2006].

HENTTONEN, H. & HANSKI, I. 2000. Population dynamics of small rodents in northern Fennoskandia. *In*: PERRY, J. N., SMITH, R. H., WOIWOD, I. P. & MORSE, D. R. (eds) *Chaos in Real Data. The Analysis of Non-Linear Dynamics from Short Ecological Time Series*. Kluwer Academic Publishers, Dordrecht, 73–95.

HOLLAND, J. H. 1998. *Emergence: From Chaos to Order.* Oxford University Press, Oxford.

HUNT, H. W. ANTLE, J. M. & PAUSTIAN, K. 2003. False determinations of chaos in short noisy time series. *Physica D*, **180**, 115–127.

JENSEN, H. J. 1998. *Self-Organized Criticality. Emergent Complex Behavior in Physical and Biological Systems.* Cambridge University Press, Cambridge.

KANTZ, H. & SCHREIBER, T. 1997. *Nonlinear Time Series Analysis.* Cambridge Nonlinear Science Series, **7**. Cambridge University Press, Cambridge.

KUPFER, J. A. & CAIRNS, D. M. 1996. The suitability of montane ecotones as indicators of global climatic changes. *Progress in Physical Geography*, **20**, 253–272.

MALAMUD, B. D. 2004. Tails of natural hazards. *Physics World*, **17**, 31–35.

MALAMUD, B. D. & TURCOTTE, D. L. 1999. Self-affine series: measures of weak and strong persistence. *Journal of Statistical Planning and Inference*, **80**, 173–199.

MALAMUD, B. D. & TURCOTTE, D. L. 2000. Cellular-automata models applied to natural hazards. *IEEE Computing in Science and Engineering*, **2**, 42–51.

MALAMUD B. D., TURCOTTE, D. L., GUZETTI, F. & REICHENBACH, P. 2004. Landslide inventories and their statistical properties. *Earth Surface Processes and Landforms*, **29**, 687–711.

MEAKIN, P. 1998. *Fractals, Scaling and Growth Far From Equilibrium.* Cambridge Nonlinear Science Series, **5**. Cambridge University Press, Cambridge.

MOSER, M. 2003. Geotechnical measurements for assessment of the kinematic and long-term behaviour of unstable mountainsides. *In*: NATAU, O., FECKER, E. & PIMENTEL, E. (eds) *Geotechnical Measurements and Modelling – Proceedings of the International Symposium on Geotechnical Measurements and Modelling*, 23–25 September 2003, Karlsruhe, Germany. A.A. Balkema, 217–223.

MOSER, M., MEIER, H., LOTTER, M. & WEIDNER, S. 2002. Geotechnical aspects of deep-seated mass movements in Austria. *In*: RYBÁŘ, J. (ed.) *Landslides – Proceedings of the 1st European Conference on Landslides*, Prague, Czech Republic, 24–26 June 2002. Swets & Zeitlinger, Lisse, 423–430.

MÜLLER, L. 1980. Aktuele Fragen auf dem Grenzgebiet zwischen Ingenieurgeologie im Zeitalter der Umweltzerstöring. *Geologishes Rundschau*, **66**, 723–739.

NICHOLIS, G. & PRIGOGINE, I. 1977. *Self-Organisation in Non-Equilibrium Systems.* John Wiley, New York.

NYCHKA, D., ELLNER, S., MCCAFFREY, D. & GALLANT, A. R. 1992. Finding chaos in noisy systems. *Journal of the Royal Statistical Society B*, **54**, 399–426.

PALUŠ, M. 1995*a*. Coarse-grained entropy rates for characterization of complex time series. *Physica D: Nonlinear Phenomena*, **93**, 64–77.

PALUŠ, M. 1995*b*. Testing for nonlinearity using redundancies: quantitative and qualitative aspects. *Physica D: Nonlinear Phenomena*, **80**, 186–205.

PALUŠ, M. & NOVOTNÁ, D. 1998. Detecting modes with nontrivial dynamics embedded in colored noise: enhanced Monte Carlo SSA and the case of climate oscillation. *Physics Letters A*, **248**, 191–202.

PALUŠ, M. & STEFANOVSKA, A. 2003. Direction of coupling from phases of interacting oscillators: an information-theoretic approach. *Physical Review E*, **67**, 055201 (R), 4.

PALUŠ, M., KOMÁREK, V. *ET AL.* 2001. Synchronization as adjustment of information rates: detection from bivariate time series. *Physical Review E*, **63**, 046211.

PALUŠ, M., NOVOTNÁ, D., & ZVELEBIL, J. 2004. Fractal rock slope dynamics anticipating collapse. *Physical Review E*, **70**, 036212, 7.

PENG, C. K., BULDYREV, S. V., HAVLIN, S., SIMONS, M., STANLEY, H. E. & GOLDBERGER, A. L. 1994. Mosaic organization of DNA nucleotides. *Physical Review E*, **49**, 1685–1689.

PENG, C. K., HAVLIN, S., STANLEY, H. E. & GOLDBERGER A. L. 1995. Quantification of scaling and crossover phenomena in nonstationary heartbeat time series. *Chaos*, **5**, 82–87.

PERRY, J. N., SMITH, R. H., WOIWOD, I. P. & MORSE, D. R. (eds) 2000. *Chaos in Real Data. The Analysis of Non-Linear Dynamics from Short Ecological Time Series.* Kluwer Academic Publishers, Dordrecht.

PHILLIPS, J. D. 1999. *Earth Surface Systems, Complexity, Order and Scale.* Blackwell, Oxford.

PIKOVSKY, A., ROSENBLUM, M., & KURTHS, J. 2003. *Synchronization. A Universal Concept in Nonlinear Science.* Cambridge Nonlinear Science Series, **12**, Cambridge University Press, Cambridge.

POISEL, R. & PREH, A. 2004. Rock slope initial failure mechanisms and their mechanical models. *Felsbau*, **22**, 45–50.

POISEL, R. & ROTH, W. 2004. Run out models of rock slope failures. *Felsbau*, **22**, 46–50.

PRIGOGINE, I. & STENGERS, I. 1984. *Order Out of Chaos; Man's New Dialogue with Nature.* Bantam Books, New York.

ROCHET, L. 1992. Acultation – Diagnostic – Surveillance. *Bulletin IAEG*, **45**, 43–57.

RŮŽEK, B. & ZVELEBIL, J. 1993. Numerical analysis of time series obtained by rock slope monitoring. *In*: NOVOSAD, S. & WAGNER, P. (eds) *Landslides. Proceeding of Seventh International Conference and Field Workshop on Landslides*. A.A. Balkema, Prague, 175–184.

RYBÁŘ, J. 1999. Climatic influence on development of landslides and other dangerous slope movements (in Czech). *Geotechnické dny, Informační*. Centrum ČKAIT, Praha.

RYBÁŘ, J. 2004. Landslides and other dangerous slope movements in the area of Czech Republic (in Czech). *Český Časopis Fyzikální*, **54**, 254–257.

SAITO, M. 1969. Forecasting time of slope failure by tertiary creep. *Proceeding of 7th ICSMFE*, Mexico City, **2**, 677–683.

SCHERTZER, D. & LOVEJOY, S. (eds) 1991. *Non-Linear Variability in Geophysics. Scaling and Fractals*. Kluwer, Dordrecht.

SCHMIDT, J. & DIKAU, R. 2004. Modelling historical climate variability and slope stability. *Geomorphology*, **60**, 433–447.

SCHMITZ, A. & SCHREIBER, T. 1999. Testing for nonlinearity in unevenly sampled time series. *Physical Review E*, **59**, 4044–4047. The routine randomize-uneven can be obtained from http://www.mpipks-dresden.mpg.del~tisean/. [Accessed 1 July 2006].

SIVAKUMAR, B. 2004. Chaos theory in geophysics: past, present and future. *Chaos, Solitrons and Fractals*, **19**, 441–462.

SORNETTE, D., HELMSTETTER, A., ANDERSON, J. V., GLUZMAN, S., GRASSO, J. R. & PISARENKO, V. 2004. Towards landslide predictions: two case studies. *Physica A*, **338**, 605–632.

TAUSCH, R. J., WIGAND, P. E. & BURKHARDT, J. W. 1993. Plant community thresholds, multiple steady states, and multiple successional pathways: legacy of Quaternary? *Journal of Range Management*, **46**, 439–447.

TERZAGHI, K. 1962. Stability of steep slopes on hard unweathered rocks. *Géotechnique*, **4**.

TURCOTTE, D. L. 1989. Fractals in geology and geophysics. *Pure and Applied Geophysics*, **131**, 171–196.

TURCOTTE, D. L. 1997. *Fractals and Chaos in Geology and Geophysics*, 2nd edn. Cambridge University Press, Cambridge.

TURCOTTE, D. L. & RUNDLE, J. B. 2002. Self-organized complexity in the physical, biological, and social sciences. *Proc. Natl. Acad. Sci. USA*, **99** (Suppl. 1), 2530–2537.

VAŘILOVÁ, Z. & ZVELEBIL, J. 2005. Sandstone relief geohazards and their mitigation: rock fall risk management in the Bohemian Switzerland national park. *Ferrantia*, **44**, 51–55.

VILES, H. 2001. Scale issues in weathering studies. *Geomorphology*, **41**, 63–72.

VLČKO, J. 2004. Extremely slow slope movements influencing the stability of Spiš Castle, UNESCO site. *Landslides*, **1**, 67–71.

VOIGHT, B. & KENNEDY, B. A. 1979. Slope failure of 1967–1969, Chuquicamata mine, Chile. *In*: VOIGHT, B. (ed.) *Rockslides and Avalanches* 2. Elsevier: Amsterdam, 595–632.

ZAVORAL, J. 2002. Remedial measures on unstable rock objects in Hřensko village (in Czech). *Geotechnika*, **3**, 13–16.

ZVELEBIL, J. 1985. Time prediction of a rock fall from a sandstone rock slope. *In*: *Proceeding of 4th International Symposium on Landslides*. Toronto University Press, Toronto, **3**, 93–96.

ZVELEBIL, J. 1989. Engineering-geological aspects of rock slope development in Děčín Highland, NW Bohemia (in Czech). PhD thesis, Charles University, Prague.

ZVELEBIL, J. 1995. Determination of characteristic features of slope movements present day activity by monitoring in thick-bedded sandstones of the Bohemian Cretaceous Basin. *Acta Universitatis Carolinae, Geographica*, Supp., 79–113.

ZVELEBIL, J. 1996. A conceptional phenomenological model to stability interpretation of dilatometric data from rock slope monitoring. *In*: SENESET, K. (ed.) *Landslides. Proceeding of 7th International Symposium on Landslides*. Balkema, Rotterdam, 1473–1480.

ZVELEBIL, J. & MOSER, M. 2001. Monitoring based time-prediction of rock falls: three case-histories. *Physics and Chemistry of the Earth (B)*, **26**, 159–167.

ZVELEBIL, J. & PARK, H. D. 2001. Rock slope monitoring for environment – friendly management of rock fall danger. *In*: SASSA, K. & FUKUOKA, H. (eds) *Proceeding of UNESCO/IGCP Symposium on Landslide Risk Mitigation and Protection of Cultural and Natural Heritage*, Tokyo, 199–209.