Short time scale laws in self-potential signals from two different seismically active Mediterranean areas (the Southern Apennine chain and Crete Island)

Gerardo Colangelo (1), **Maria Lanfredi** (1) (4), **Vincenzo Lapenna** (1), **Maria Macchiato** (2) (4) **and Filippos Vallianatos** (3)

(1) *Istituto di Metodologie Avanzate di Analisi Ambientale, CNR, Tito Scalo (PZ), Italy*
(2) *Dipartimento di Scienze Fisiche, Università «Federico II», Napoli, Italy*
(3) *Technological Educational Institute of Crete, Greece*
(4) *Istituto Nazionale per la Fisica della Materia, Unità di Napoli, Italy*

Abstract
Self-potential time series are investigated to characterise self-potential time scales. The data analysed were recorded in stations located in two active seismic areas of the Mediterranean region, the Southern Apennine chain (Giuliano) and Crete Island (Heraklion), where in past and recent years many destructive seismic events have taken place. The seismological and geological settings, combined with a low level of cultural noise, allow us to consider these areas ideal outdoor laboratories to study the time dynamics of geophysical parameters of electrical nature. At the same time, the different seismological features of such areas make an inter-comparison between the geoelectrical variability observed at the two sites interesting. Fractal analysis tools, able to detect scale laws and quantify persistence features, are used to better understand the background variability properties of the self-potential signals. As results from our analysis, antipersistence seems to be a ubiquitous feature on short time scales (minutes) regardless of environmental conditions. On such scales, the accumulation of random fluctuations is not particularly efficient and significant variations mostly occur as sudden jumps.

Key words *self-potential – earthquake prediction – structural analysis – fractals – anomalous diffusion*

1. Introduction

Seismic activity and geolectrical variability are likely driven by some common geophysical mechanisms, such as the variability of the stress and fluid fields (*e.g.*, Sholtz, 1990). In the recent past, some works supported the existence of a direct link between intense seismic activity and electrical anomalies (*e.g.*, Varotsos *et al.*, 1993; Uyeda, 1996; Nagao *et al.*, 1996). On the other hand, other authors suggested alternative explanations for observed anomalous electrical fluctuations (Pham *et al*, 1998) or, more in general, complained about the lack of systematic and rigorous statistical analyses in the works supporting such a hypothesis (Kagan, 1996; Mulargia, 1997, Stark, 1997; Geller, 1999). Only recently have theoretical models been suggested

Mailing address: Dr. Maria Lanfredi, Istituto di Metodologie Avanzate di Analisi Ambientale, CNR, C. da S. Loya, 85050 Tito Scalo (PZ), Italy; e-mail: Lanfredi@na.infn.it

to explain the origin of electrical anomalies (Vallianatos and Tzanis, 1998, 1999a,b).

Apart from the striking problem of reliably assessing the existence of a significant correlation between electrical variability and seismic activity, an open question remains on the definition of anomalous pattern, which is crucial for exploring the potential of geoelectrical parameters as earthquake precursors. In fact, also supposing the existence of a significant dynamical correlation, electrical signals can be reliably used as warning signals for earthquakes only after an objective criterion is stated to classify anomalous behaviours. Otherwise one remains confined in the framework of retrospective studies.

One of the main sources of difficulty in assessing this question correctly resides in the complex nature of the system underlying geoelectricity. Geoelectrical signals and, in particular, the self-potential signals we discuss in this work, are the result of the interaction between very heterogeneous and not well known mechanisms which are constrained by a large variety of boundary conditions. Complex dynamics and external variability (rainfalls, temperature variations, etc.) may produce crinkled behaviours, irregularity and details over a wide range of time scales.

The presence of a large variety of dynamical behaviours makes it particularly hard to discriminate the patterns due to anomalous conditions from the standard ones. In addition, local features peculiar to the given geological setting, can be actively involved in driving electrical variability (Patella *et al.*, 1997). As a consequence, many problems concerning geoelectricity and its link with seismicity might be a matter of local concern and *a priori* one cannot exclude that some details about the definition itself of «anomaly» have to be case-specific.

Recently, self-potentials measured at two sites, Tito and Tramutola, located on the Irpinia-Basilicata Apennines (Italy) were analysed (Cuomo *et al.*, 2000). Antipersistent features were disclosed on the time scales going from a few minutes to several hours. If seen at a temporal detail of minutes or hours, the analysed signals do not show significant accumulation of random fluctuations. They do not form easily fast trends, appear rather noisy, and generally some days are needed to pick up the presence of possible smooth behaviours.

In this work we investigate the short time persistence features of self-potential time series recorded respectively in a different site (Giuliano) located in the Irpinia-Basilicata region itself and in a site (Heraklion) located on the Crete Island (Greece) which exhibits seismic features different from those of the Southern Apennine chain both for frequency and intensity of earthquakes. Persistence properties are characterised by analysing the second order structure function (Mandelbrot and van Ness, 1968) of the time series and discussed exploiting the analogy of our results with those expected in anomalous diffusion phenomena.

2. Data

The data we analyse in this work are sequences of voltage differences measured using a receiving electrode array. Data were recorded from 1-1-1993 to 12-31-1993 at Heraklion station (Crete) and from 1-1-1998 to 12-31-1998 at Giuliano station (Southern Italy).

2.1. *Giuliano station*

This station is equipped with a high resolution multimeter connected with a GPIB interface to a computer, the sensors are two electrodes of a dipole aligned with the fault direction, the distance between the probes is 100 m and they are built with copper bars and are put into the ground at 1 m depth to avoid the influence of temperature excursions. The electrodes are connected with screened trailing cables to the multimeter. The sampling interval is $\Delta t = 1$ s and after a preliminary screening of the experimental values a mean value every 60 samples is stored. At the Giuliano station there are only two electrodes to measure only a component of electric field that is parallel oriented towards the fault. This constraint was necessary to jointly measure the electrical and seismoacoustic parameters, in any case there are other stations with the classical couples of electrodes in the investigated area (Di Bello *et al.*, 1994).

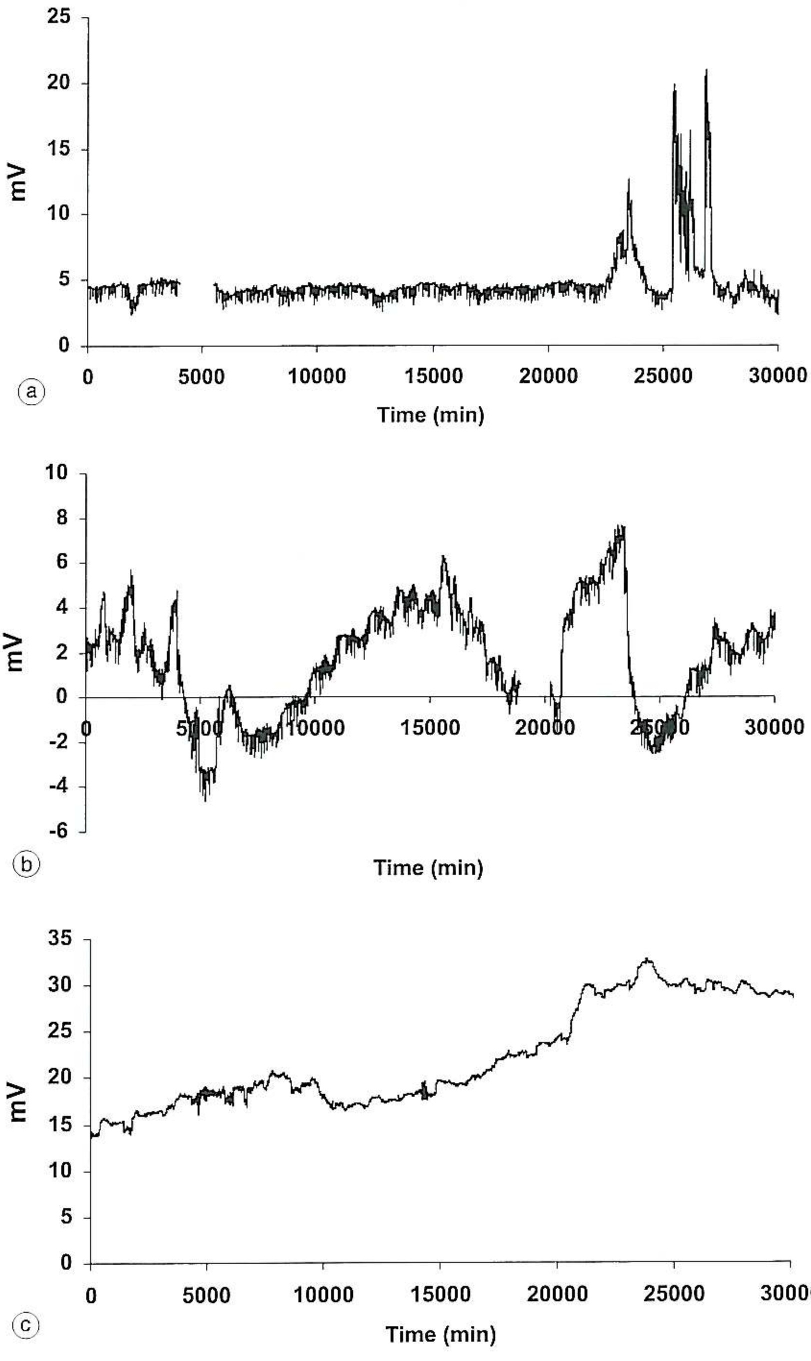

Fig. 1a-c. Examples of records of self-potential signals. The sampling time is 1 min and the plots cover about a period of 20 days. a) Giuliano (January 1998); b) Giuliano (May 1998); c) Heraklion (June 1993).

2.2. *Heraklion station*

At the field station (Heraklion, Crete island) we measured the telluric field variations (from 0.1 Hz to DC), by two pairs of dipoles oriented in EW and NS directions. The length of dipoles, in each pair, is 50 m and 100 m, respectively. In our instrumentation a Butterworth low-pass active filter with a cut-off frequency of 0.1 Hz at – 3 dB, is used (see for details Nomicos and Chatzidiakos, 1993). The station is installed 20 km from the coast and is far enough from any industrial noise source, as it was selected after an extensive investigation. The field system is based on a data-logger (model 21X, Campbell Scientific) installed at the field station, which digitises the information and stores it. The sampling rate was set to one sample per second. A central station uses a commercial PC to communicate twice per day with data-logger and collects the information via switched telephone line, using a standard CCITT smart modem V21/V22. Data are saved on hard disk of the central station, for further processing.

2.3. *Data records*

Examples of geoelectrical records measured at the two sites are shown in fig. 1a-c. Very different behaviours can be detected along self-potential time series. Sudden changes, long time stationary behaviours, similar oscillatory patterns and smooth trends can be observed in geoelectrical variability. We emphasise that each of the behaviours shown in fig. 1a-c are not peculiar to the time series they were extracted from but both the series show a similar variety of dynamical behaviours.

It is well known that some environmental parameters can be responsible for self-potential variability. In our measuring systems, the electrodes were placed into the ground at least 1 m depth, consequently the influence of temperature on self-potential data is negligible. It is well known that the influence of environmental temperature is relevant only in the shallow layers (depth less than 1 m) of subsoil. The correlation between the environmental and rock temperature available at Giuliano station with self-potential data is about $r \approx 0.2$.

Rain and water infiltration in the shallow layers of subsoil can induce electrokinetic phenomena. As a consequence, self-potential measured by means of electrodes in the ground are generally contamined during the rain period. Observational evidence suggests that this effect is more significant when we have rain after a long dry period. As an example, fig. 2 shows rain at Giuliano in January 1998, when the time series in fig. 1a was recorded. To the naked eye, it is very easy to note the resemblance between the two plots. It has to be stressed that the signal in fig. 1c was recorded at the beginning of the

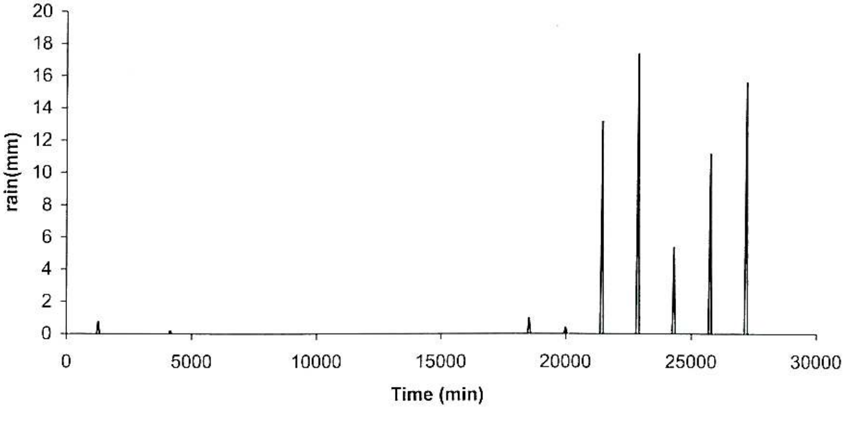

Fig. 2. Rain events during January 1998 at Giuliano.

Crete dry season, when weather conditions are characterised by high air temperature and no rain (on the average about 24 °C and 1.5 mm respectively in the period June-October 1993).

3. The analysis tools

Irregularity, crinkliness, and jagged patterns in observational signals are generally the signature of complex dynamics. Fractal analysis methods usually are suitable tools to quantify such an irregularity and to gain insight into the complexity of the dynamics underlying a given signal. Fractal processes have no characteristic scale and their power spectrum follows a power law $1/f^{\beta}$ (Feder, 1988). Pure $1/f^{\beta}$ power spectra, that is pure fractal processes are physically impossible (see, *e.g.*, Theiler, 1991) because the total power would diverge to infinity. Low and high cutoffs have to be expected which makes band-limited fractal behaviours in real time series and, more in general, multi-scaling behaviours may be expected.

One of the tools universally accepted to investigate scale invariance in space and time and, in particular, to analyse fractional Brownian motion (the fractal extension of the classical Brownian motion) is structural analysis (Mandelbrot and van Ness, 1968).

The structure function of order p of a time series $\{x(n)\}$ $(n = 1, \ldots N)$ is defined according to

$$S_p(\tau) = < \| x(n + \tau) - x(n) \|^p >$$

with the vertical bars denoting the Euclidean norm and the angular brackets the expected value.

In particular, for fractional Brownian motions (fBm), $S_p(\tau)$ scales as $\tau^{\alpha(p)}$

$$S_p(\tau) \propto \tau^{\alpha(p)}.$$

In this work, we focus on the second order structure function, which can provide useful information on the persistence properties of the investigated signal and is usually exploited in the dynamic description of reaction-diffusion systems (Zanette, 1998).

For any real number H in the range $0 < H < 1$, let $B_H(t)$ be the position of a particle performing an fBm. The increments of a fBm have zero average

$$< B_H(t) - B_H(t_0) > = 0$$

and variance

$$<[B_H(t) - B_H(t_0)]^2> \sim |t - t_0|^{2H}$$

that is the second order structure function of fBm scales as

$$S_2(\tau) \sim \tau^{2H}$$

with the coefficient H (Hurst coefficient) related to the spectral exponent by the following formula (Mandelbrot and van Ness, 1968):

$$\beta = 2H + 1.$$

The increments of a fractional Brownian motion are stationary and their correlation coefficient obeys the law (*e.g.*, Vicsek, 1968)

$$\rho(H) \propto (2^{2H-1} - 1).$$

For $H = 0.5$ there is no correlation between the process increments and we are in a standard diffusive regime. As is well known, in the random walk which models classical Brownian diffusion the walker follows a random path driven by a memoryless dynamics.

FBm well describes transport processes, referred to as anomalous diffusion phenomena, which are closely related to standard diffusion and are commonly detectable in the natural world (Zanette, 1998 and references therein). In such transport phenomena, the mean square displacement does not depend linearly on time, as in standard diffusion, but grows as a power law with a scaling coefficient different from the value $H = 0.5$. By exploiting the analogy with anomalous diffusion, some dynamical inferences can be drawn from a scaling second order structure function of a generic signal, also in the case it is not generated by fBm and there is no simple relation between the spectral and Hurst coefficients.

A positive correlation characterises superdiffusive regimes ($H > 0.5$). Positive (negative) trends follow positive (negative) trends and the accumulation of fluctuations is faster than in classical Brownian motion. The motion is persistent and accounts for a transport more efficient than in normal diffusion. Signals which show scaling in the superdiffusive range are strongly non stationary, they form trends and display long-range correlation whose strength increases with H, the limit $H = 1$ value being the clue of an analytical drift.

Conversely, a negative correlation ($H < 0.5$) indicates that positive fluctuations follow negative fluctuations and *vice-versa*. In such subdiffusive signals, the variance of the mean square displacement grows slower than in standard diffusion. At the limit $H = 0$ it does not grow at all and the signal is stationary.

To summarize, H characterises the persistence properties of the time series according to the following scheme:

– H = 0.5 – classical Brownian motion (standard diffusion); the process is dynamically memoryless.

– $0.5 < H < 1$ – persistent motion (superdiffusion); future trends are positively correlated with past trends.

– $0 < H < 0.5$ – antipersistent motion (subdiffusion); future trends are negatively correlated with past trends.

In this work second order structure function is estimated by (*e.g.*, Cressie, 1993):

$$\hat{S}_2(\tau) = \frac{1}{N(\tau)} \sum_{N(\tau)} (x(t+\tau) - x(t))^2$$

where $N(\tau)$ is the number of observations displaced at a time distance τ apart. Note that the time series do not need to be sampled at equal time intervals and a lack of information in periods which are short in comparison with the length of the series, are expected not to affect dramatically the characterisation of background behaviours.

4. Results

In order to take into account different seasonal conditions, second-order structure function was estimated separately from monthly data samples (months with very few available data were discharged) in the time range going from a few minutes up to ten days. The presence of antipersistent scaling on the shortest time scales (minutes) was detected in all 19 samples investigated. In particular, fig. 3a-c shows the log-log plots of $S_2(\tau)$ estimated from the records of fig. 1a-c. A scaling typical of antipersistence is detectable over about a decade in the first part of the plot in fig. 3a ($H = 0.350 \pm 0.006$). This scaling is followed by a standard diffusion power law ($H = 0.495 \pm 0.002$) and finally $S_2(\tau)$ attains to a plateau indicative of stationariety ($H = 0.0200 \pm 0.0004$). The sample appears as a succession of short range correlated fluctuations with antipersistence properties characterising the shortest time scales. As shown in Section 2.3, such fluctuations were related to rain events (comparison between fig. 1a and fig. 2). In any case, the estimation of the Hurst coefficient over the shortest time scales in the dry period ($H = 0.380 \pm 0.008$) is statistically consistent with that calculated in the rain period ($H = 0.345 \pm 0.008$).

Figure 3b shows two slightly antipersistent ranges ($H = 0.453 \pm 0.005$ and $H = 0.478 \pm$ ± 0.0008). In the final part of the plot, the pattern described by $S_2(\tau)$ starts to decrease as a consequence of the oscillatory behaviour observed in fig. 1b. At any rate, similar time scale properties are displayed by the two samples in fig. 1a and 1b over the time range examined.

Three time ranges in which scaling occurs are detectable in fig. 3c, with three different dynamical characteristics: on the shortest time scales the series is antipersistent ($H = 0.355 \pm$ ± 0.001), in the intermediate range the time series evolves as a classical Brownian motion ($H = 0.501 \pm 0.002$) and finally a slight persistence is detectable on longer time scales ($H = 0.632 \pm 0.0004$). Persistence accounts for the very smooth trend which can be picked up in fig. 1b at the naked eye view. The dynamical correlation characterising persistence suggests the presence of a driving forcing. In spite of this forcing, also in this case the degree of irregularity increases on shorter time scales and the presence of anticorrelated increments is detectable on the shortest ones. To sum up, antipersistence on short time scales (minutes) characterises both the time series recorded at Giuliano and that recorded at Heraklion.

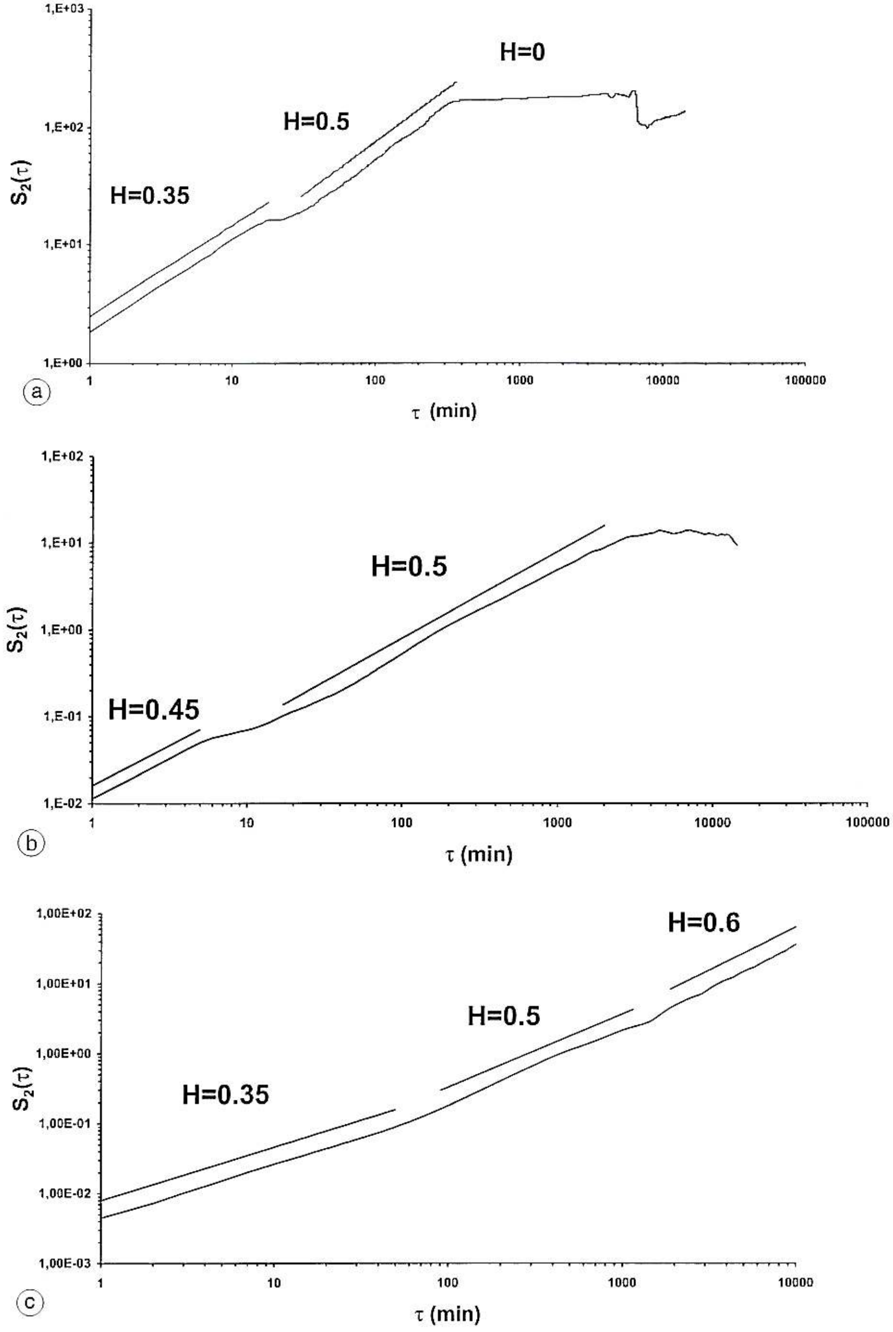

Fig. 3a-c. Second order structure function estimated from the records of fig. 1a-c in log-log scale. The time scales investigated range from 1 min to ten days. a) Giuliano (January 1998); b) Giuliano (May 1998); c) Heraklion (June 1993).

5. Discussion and conclusions

The ubiquity of antipersistent features on the short time scales (minutes) found in our analysis agrees with previous results (Cuomo *et al.*, 2000) and accounts for a slightly non stationary, noisy behaviour. Short time variations are similar to those expected in reaction-diffusion systems with subdiffusive properties. Smooth trends present in the series appear rather slow. There is no significant accumulation of fluctuations in the variability played on short time scales where possible significant changes mostly occur as sudden variations. Slightly non stationary, fast correlated fluctuations are not dynamically anomalous but are compatible with the background behaviour shown by the signals (although they might show anomalous amplitude). On longer time scales a wide variety of behaviours is detectable along the series. In particular, two extreme behaviours were observed. Second order structure function estimated from the sample recorded at Giuliano in January 1998 quickly attains a flat behaviour accounting for stationary features, whereas that estimated from the sample recorded at Heraklion in June 1993 attains a superdiffusive scaling. In the latter case, long range dynamical correlation is detectable in the observations and the accumulation of fluctuations spreads faster than in normal diffusion. This behaviour is presumably driven by the progressive drought which characterises Crete Island in that period. As is well known, the signals are very sensitive to the humidity level of the soil and a slow progressive decrease of the water content can likely be responsible for a smooth trend. In any case, also from the comparison of these extreme examples, no significant dynamical difference is detectable on the shortest time scales which overall behave as in a subdiffusive phenomenon.

REFERENCES

CRESSIE, N.A.C. (1993): *Statistic for Spatial Data* (John Wiley & Sons, New York), p. 900

CUOMO, V., M. LANFREDI, V. LAPENNA, M. MACCHIATO, M. RAGOSTA and L. TELESCA (2000): Antipersistent dynamics in short time scale variability of self-potential signals, *Ann. Geofis.*, **43** (2), 271-278.

DI BELLO, G., V. LAPENNA, C. SATRIANO and V. TRAMUTOLI (1994): Self-potential time series analysis in a seismic area of the Southern Apennines: preliminary results. *Ann. Geofis.*, **37** (suppl. n. 5), 1137-1148.

FEDER, E. (1988): *Fractals* (Plenum Press, New York), p. 181.

GELLER, J. (1999): in *Is the Reliable Prediction of Individual Earthquakes a Realistic Scientific Goal?* (online Nature Debates helix.nature.com/debates/earthquake/equake_ frameset.html).

KAGAN, Y.Y. and D.D. JACKSON (1996): Statistical tests of VAN prediction: comments and reflections, *Geophys. Res. Lett.*, **23**, 1433-1436.

MANDELBROT, B.B. and J.W. VAN NESS (1968): Fractional Brownian motions, fractional noises and applications, *SIAM Rev.*, **10** (4), 422-437.

MULARGIA, F. (1997): Retrospective validation of the time association of precursors, *Geophys. J. Int.*, **131**, 500-504.

NAGAO, T., S. UYEDA, Y. ASAI and M. KONO (1996): Anomalous changes in geoelectric potential preceding four earthquakes in Japan, in *Sir. J. Lighthill, «A Critical Review of VAN»* (Word Scientific), 292-300

NOMICOS, K. and P. CHATZIDIAKOS (1993): A telemetric system measuring electrotelluric variations in Greece and its application to earthquake prediction, *Tectonophysics*, **224**, 39-46.

PATELLA, D., A. TRAMACERE and R. DI MAIO (1997): Modelling earth current precursors in earthquake prediction, *Ann. Geofis.*, **40** (2), 495-518.

PHAM, V.N., D. BOYER, G. CHOULARIAS, J.L. LE MOUËL, J.C. ROSSIGNOL and G.N. STAVRAKAKIS (1998). Characterisitcs of electromagnetic noise in the Ioannina region (Greece); a possible origin for so called «Seismic Electric Signal» (SES), *Geophys. Res. Lett.*, **25** (12), 2229-2232.

SCHOLTZ, C.H. (1990): *The Mechanics of Earthquakes and Faulting*. (Cambridge University Press), pp. 439.

STARK, P.B. (1997): Earthquake prediction: the null hypothesis, *Geophys. J. Int.*, **131**, 459-499.

THEILER, J. (1991): Some comments on the correlation dimension of $1/f^{\alpha}$ noise, *Phys. Lett. A* **159** (8), 9480-9493.

UYEDA, S. (1996): Introduction to the VAN method of earthquake prediction, in *Sir. J. Lighthill, «A Critical Review of VAN»* (Word Scientific), 3-28.

VALLIANATOS, F. and A. TZANIS (1998): Electric current generation associated with the deformation rate of a solid: preseismic and coseismic signals, *Phys. Chem. Earth*, **23** (9-10), 933-939.

VALLIANATOS, F. and A.M. TZANIS (1999a): A model for the generation of precursory electric and magnetic fields associated with the deformation rate of the earthquake focus in, *Seismic Atmospheric and Ionospheric Electromagnetic Phenomena* (Terra Sci. Publ. Co., Tokyo).

VALLIANATOS, F. and A. TZANIS A. (1999b): On possible scaling laws between Electric Earthquake Precursors (EEP) and earthquake magnitude, *Geophys. Res. Lett.*, **26** (13), 2013-2016.

VAROTSOS, P., K. ALEXOPOULOS and M. LAZARIDOU (1993): Latest aspect of earthquake prediction in Greece based on seismic electric signals, *Tectonophysics*, **224**, 99-125.

VICSEK, T. (1989): *Fractal Growth Phenomena* (World Scientific, Singapore, New Jersey), pp. 354.

ZANETTE, D.H. (1998): Statistical-thermodynamical foundations of anomalous diffusion, *Physica A*, **252**, 159.