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Extracting quantitative dynamics from ^{222}Rn gaseous emissions of mud volcanoes

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SUMMARY

In this work we explore the inner time dynamics of ^{222}Rn gaseous emissions of a bubbling mud volcano located in northern Apennines (Italy). In order to discriminate shallow environmental effects, barometric and temperature series have been also monitored and compared with ^{222}Rn data. The Lomb periodogram and the Higuchi techniques have been applied to characterize the time dynamics of the experimental time series. No significant periodicity has been identified and the power spectrum is characterised by a monotonic decrease with frequency f which follows a typical power law ($\propto f^{-\alpha}$). Our findings suggest to consider the ^{222}Rn time series as a realization of an antipersistent stochastic process. This indicates that the dynamics underlying Radon emissions from bubbling mud volcanoes is complex and that a relatively large number of unknown factors control the process. This result discourages the use of bubbling gaseous emissions for the monitoring of geodynamic processes. Copyright © 2003 John Wiley & Sons, Ltd.

KEY WORDS: mud volcanoes; power spectrum; scaling

1. INTRODUCTION

A classical problem in earth science is the extraction of qualitative and quantitative dynamical information from irregular time series coming from the monitoring network. In particular, the problem consists in obtaining information about the physics underlying the geodynamic process only from the analysis of measured time series. The modern theory of complex dynamical systems allows us to select a wide class of methodologies that could be potentially applied to solve this problem by the analysis of geophysical and geochemical time series without any a *priori* assumptions about the geodynamic process that produces the observable signals on the earth's surface (e.g. Feder, 1989; Turcotte, 1995, and references therein).

In recent years, more advanced methods have been proposed and applied in many different fields of earth sciences (e.g. earthquake dynamics, volcanic phenomena, El-Niño fluctuations, geomagnetic reversals, etc.) and they have given an important contribution to the detection of deterministic,

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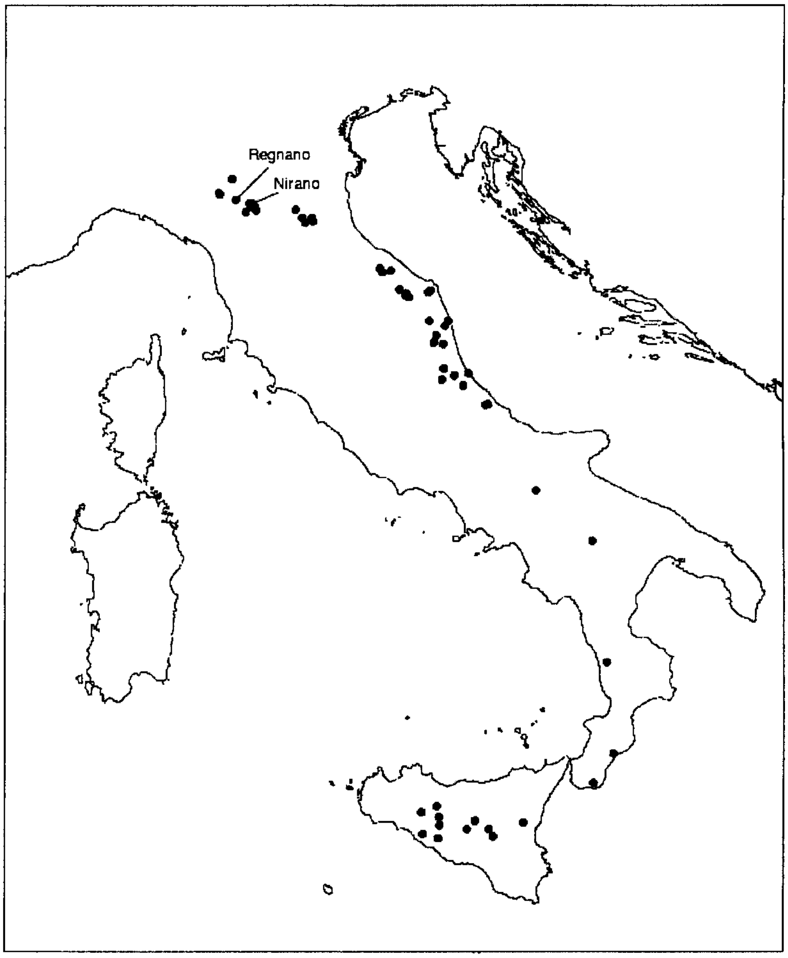

Figure 1. Map of the Italian mud vulcanoes. The measuring station at station Regnano is indicated

stochastic and/or chaotic behaviours in many geophysical processes (e.g. Bak and Tang, 1989; Turcotte, 1995; Cortini and Barton, 1994; Cuomo *et al.*, 1994; Cuomo *et al.*, 1996; Cuomo *et al.*, 1999). In particular, the search of scaling laws in power spectra discloses the possibility to discriminate stochastic behaviours and to obtain information about the physical process underlying the generation mechanism of observational data.

The main goal of this article is to explore the inner dynamics of a ^{222}Rn time series measured by means of a remote station located near a mud volcano located on the Northern Apennine chain (Figure 1) large accretionary complex, whose neogenic activity is widely documented (see, for example, Castellarin and Vai, 1987).

Mud volcanoes are typical expressions of accretionary complexes, in particular along continental margins (Higgins and Saunders, 1974; Le Pichon *et al.*, 1990). Ramberg (1973) showed that mud volcanism is produced when a layered sequence of soft material is arranged in a sequence with inverted density (the densest layers being at the top). Mud is driven upward by buoyancy forces arising

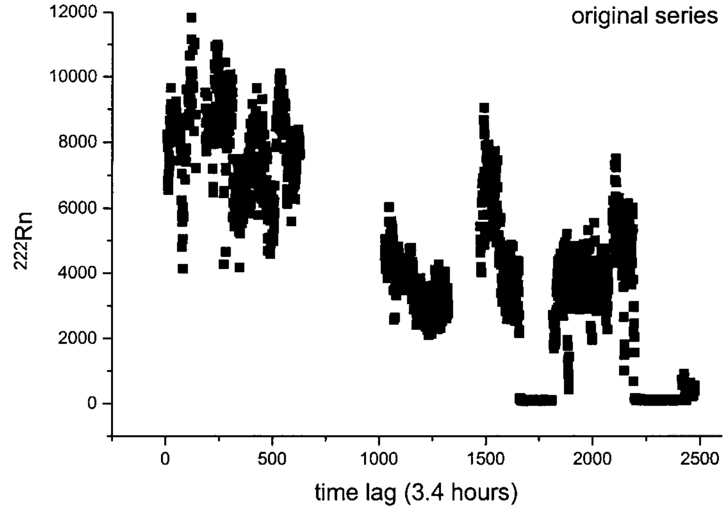

Figure 2. Original ^{222}Rn data measured in Regnano mud volcano

from the bulk density contrast between an overpressured muddy mass and an overburden of greater density (Brown, 1990).

Morphostructural features and geochemical evidences allow us to consider mud volcanoes as representative of confined fluid reservoirs, located along tectonic disturbancies (Martinelli, 1999). Eruptive products are clay muds, connate salty waters and gases (mainly methane). Temperature of extruded fluids in general reflects shallow environmental temperature, but in some cases thermal anomalies have been observed in concomitance with paroxysmal eruptions. Tamrazyan (1972) identified a particular sensitivity of mud volcanism to earth tides. This led to the hypothesis that physical changes in the earth strain field as the ones produced by seismogenic processes could be expressed as fluctuations in mud volcano activity.

By the analysis of radon data recorded in the liquid phase of waters expelled from the Nirano mud volcano in the Northern Apennines (Figure 1), Martinelli *et al.* (1995) evidenced a significant sensitivity of mud volcanoes to geodynamic phenomena. In order to better explore this phenomenon, on 1990 an automatic radon monitoring station using a Pylon decaying chamber has been placed on the main vent of the Regnano mud volcano (Figure 1). The experimental setting is partially described in Martinelli and Ferrari (1991). By means of this apparatus, gaseous emissions resulting from bubbling activity have been monitored nearly continuously for 1 year (Figure 2).

In this work we investigated the nature of temporal fluctuations in ^{222}Rn time series measured at the Regnano site. After removing possible spurious fluctuations induced by local meteoclimatic conditions, the residual time series has been characterized in terms of power spectra and fractal properties.

2. METHODOLOGICAL BACKGROUND

The power spectrum is the basic tool for the dynamical characterization of an experimental time series. In general, the presence of periodic fluctuations (enlightened by sharp peaks in the power spectrum) suggests an underlying dynamics characterized by a low number of degrees of freedom. Conversely, a flat power spectrum suggests that the time series results from purely random process resulting from dynamical processes characterized by a very large number of degrees of freedom. The level of predictability is quite high for the first system and null in the second one. In between these two extreme situations modern theories of dynamic processes provide a wide class of possible intermediate situations. In particular, very common in the nature is the irregular time series characterized by a monotonically decreasing power spectrum known as $1/f$ noise or flicker noise (e.g. Voss, 1989). In these situations, the power spectrum follows an $f^{-\alpha}$ power law, where f is the frequency and α is known as the 'power law index' or 'spectral index'. This pattern connotes dynamical processes characterized by a relatively large number of degrees of freedom and a certain (quite limited) degree of predictability. It is well accepted that, in these situations, the power law index can give information about the physics underlying the processes that produce the observed signals (Feder, 1989; Turcotte, 1995, and references therein).

A different description of flicker noise time series has been suggested in the pioneer study presented by Mandelbrot (1977). Here, the time series $X(t)$ is viewed geometrically as a curve, which can be considered to be self-affine when each part of it is a reduced scale image of the whole. To characterize the series, the increment function $[X(t+h)-X(t)]h^{-Hu}$ is considered as a function of h. The parameter Hu is known as the Hurst exponent and characterizes the self-affine features of the curve. The knowledge of this exponent, whose values range between 0 and 1, allows us to describe the time fluctuations of experimental data: for $Hu=0.5$ the past and future increments are completely independent (purely random noise); for $0.5<Hu\leq 1$ we have a persistent series (if the system produces increasing $X(t)$ values in one period, it is more likely to keep it increasing in the immediately following period); on the other hand, for $0\leq Hu<0.5$ we have an antipersistent series (if the system produces increasing $X(t)$ values in one period, it is more likely that it produces decreasing values in the immediately following period, and vice versa). It can be seen that the Hurst exponent is related to the power law index α by the relationship $\alpha=2Hu+1$ (Voss, 1989). Therefore, from the knowledge of power law index α it is possible to extract information about the persistence of the signal.

The value of the power law index can be computed in several ways from the original series. The simplest way is directly from the power spectrum by a simple linear regression analysis on log–log representation of the spectrum. Such estimates, however, are not sufficiently 'robust' for most applications (Higuchi, 1988). To overcome this problem, many authors have proposed other methods to construct a stable estimate of the spectral exponent. Some estimate the spectral exponent from the fractal exponent D, which is another measure of the self-affine character of a time series (Mandelbrot, 1977). In fact, it can be shown (Berry, 1979) that, for $1<\alpha<3$, $D=(5-\alpha)/2$. A stable value of the fractal dimension can be obtained by the method proposed by Higuchi (1988). A new time series X_τ^m is constructed from the original time series $X(i)$, $i=1,2,\ldots,N$,

$$X_\tau^m; X(m), X(m+\tau), X(m+2\tau), \ldots, X(m+[(N-m)/\tau]\tau); \qquad m=1,\ldots,\tau \tag{1}$$

where $[\gamma]$ indicates the integer part of γ. The length of the curve is defined as

$$L_m(t)=\left\{\left(\sum_{i=1}^{[(N-m)/\tau]}|X(m+i\tau)-X(m+(i-1)\tau|\right)\frac{N-1}{[(N-m)/\tau]\tau}\right\}\frac{1}{\tau} \tag{2}$$

The average value $<L(\tau)>$ over τ sets of $L_m(\tau)$ is defined as the length of the curve for the time interval τ. If $<L(\tau)> \propto\tau^{-\mathrm{D}}$, within the range $\tau_{\min}\leq\tau\leq\tau_{\max}$, then the curve is fractal with dimension

D in this range. Higuchi (1988) has examined the relationship between fractal dimension D and the power law index α, by calculating the fractal dimension of simulated time series which follows a single power-law spectrum density. Also in this case, the spectral exponent could be estimated using Berry's expression.

3. DATA PROCESSING

3.1. Pre-processing

Due to the particular experimental setting, the ^{222}Rn counting series in Figure 2 cannot be considered as representative of ^{222}Rn emission only. In fact, as stated above, ^{222}Rn counting has been performed by collecting gaseous emissions from a bubbling mud volcano. These gases were collected within a tank acting as a collecting chamber which covered the major eruptive mouth of the bubbling mud volcano. The exposed location of the tank made the system quite sensitive to local meteoclimatic conditions (in particular barometric and thermal). In order to evaluate actual fluctuations in ^{222}Rn emissions such effects have to be removed in advance.

A major problem during the monitoring activity was the occurrence of parossistic eruptive episodes, which in two cases were so intense to blow up the collecting tank with the consequent interruption of the Rn sampling. These episodes caused both the interruption of monitoring and the change of geometries of bubbling springs. This did not make easy the complete restoration of initial experimental settings with the consequent presence of possible biases in the final time series. Furthermore, during the last period of experimental activity, the emitting mouths are gradually displaced away from the principal mud cone with a progressive variation of gaseous emissions actually collected from the experimental apparatus. Therefore, a pre-processing phase devoted to reduce the possible biases induced in the ^{222}Rn counting series by the time varying experimental setting was necessary.

The original data set consists in three time series, respectively representative of air temperature, barometric pressure and ^{222}Rn counting, each sampled every 3.4 h for about 1 year of experimental activity. The ^{222}Rn series can be subdivided into four time segments. The first period (of about 300 days) was characterized by normal monitoring activity without significant changes in the experimental setting. This period has been followed from three time intervals (22, 31 and 9 days, respectively), each characterized by a modified experimental setting. Being representative of a distinct experimental situation, each segment has been analyzed separately from the others. In particular, for each segment, the effect of temperature and barometry on ^{222}Rn countings has been explored along with the possible presence of transient phenomena induced by the slow stabilization of experimental conditions after each re-setting of the monitoring apparatus. In order to make mutually comparable the time patterns of ^{222}Rn emission during the different time segments considered, after the removal of spurious effects, residual ^{222}Rn countings have been 'studentized', i.e. reduced to the average counting in each segment and normalized to the corresponding standard deviation. In order to remove the effects of temperature and barometric pressure we performed a linear regression on the time series recorded, priort to the application of the power spectrum and Higuchi analyses.

3.2. Dynamical characterization of the residual time series

Figure 3 shows the normalized time series of ^{222}Rn countings obtained after the pre-processing procedure. Because of missing data, the spectral analysis on this data set has been performed using the Lomb Periodogram method (Lomb, 1976), which is particularly useful when unevenly sampled time

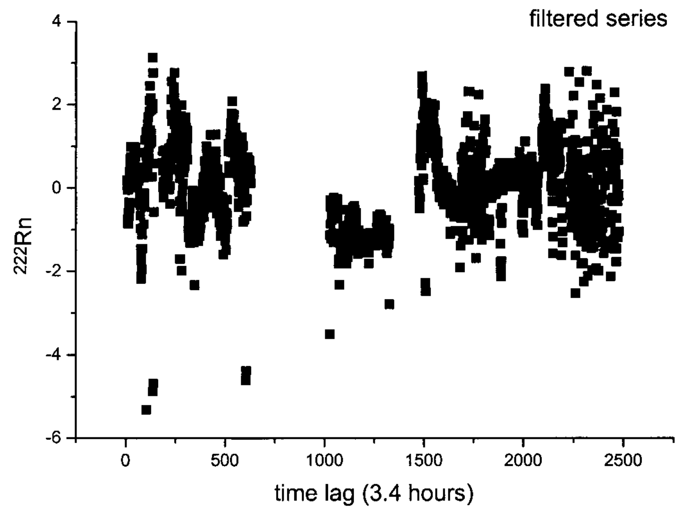

Figure 3. Standardized ^{222}Rn data filtered by the meteoclimatic and barometric components

series are considered. No significant periodicity has been identified in the resulting power spectrum (Figure 4).

This seem to exclude the possibility that tidal fluctuations can affect Rn emissions. In order to validate such conclusion, the pattern in Figure 3 has been compared with the earth tides computed by using the algorithm proposed by Longman (1959). The cross-correlation analysis performed on the two time series revealed the lack of any significant apparent interrelation between the two processes. On the other hand the monotonic decrease of power with frequency allows us to exclude the possibility that the ^{222}Rn signal is purely random (white noise). This pattern suggests the presence of a power-law

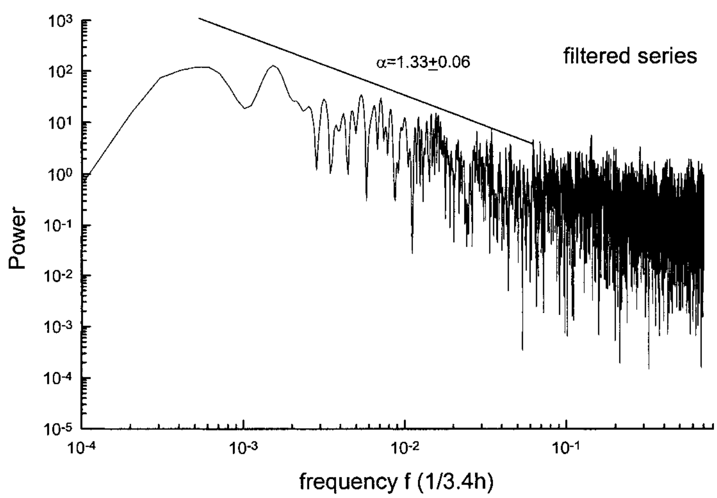

Figure 4. Log–log plot of the power spectrum density *S(f)* vs. frequency *f*, obtained with Lomb Periodogram method for the data plotted in Figure 3. The power-law behaviour of the spectrum with spectral index α obtained by the slope of line that fits the spectrum in the linear range is evident. The obtained value of the Hurst exponent suggests that the series is characterized by antipersistent temporal fluctuations

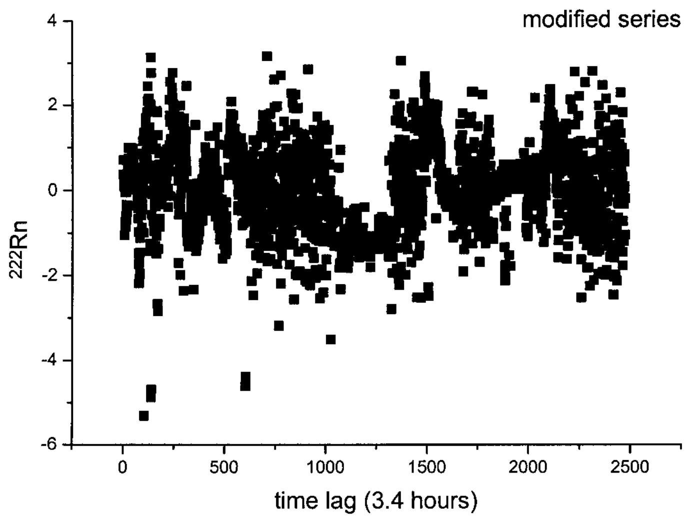

Figure 5. Example of modified series obtained filling the missing data with values randomly extracted by a Gaussian variable, having the same statistical properties of the original time series

form (coloured-noise type). A direct estimate of the power law index by the line fitting the log–log plot of the power spectrum density gives an estimate of the spectral index $\alpha = 1.33 \pm 0.06$ in the frequency range $f_{\min} = 5.06 \times 10^{-4}$ to $f_{\max} = 0.05$ in 1/3.4 h units. For frequencies larger than $f_{\max}$ the spectrum is approximately flat, as expected for a purely random process.

A further estimate of the power law index has been obtained by Higuchi fractal analysis, and we calculated the fractal dimension of the length of the time series, in accordance with (2). The slope of the line fitting the log–log plot of the length of the curve $<L(\tau)>$ vs. the time interval τ gives an estimate of the fractal dimension D, from which the power-law exponent can be calculated.

Before performing the Higuchi fractal method, we fill the gaps present in the signal with values extracted by a Gaussian random variable with the same mean and variance of the original data. To be sure that the modified series has not altered the spectral characteristics of the original series, we generated several modified series, filling the gaps with random Gaussian values; we calculated their power spectral densities and then we obtained the averaged power spectral density to compare to the power spectral density of the original series. In Figure 5 one of the modified series is presented. In Figure 6 we show both the spectrum of the original series and the averaged spectrum of the modified series: we observe that both the spectral densities are very similar, with a decreasing behaviour with the frequency; the spectral index for the modified series has been estimated in the same frequency range, that has been used to calculate the spectral exponent for the original series, obtaining $\alpha = 1.03 \pm 0.04$. The obtained value is slightly smaller than the spectral index of the original series, because we filled the data missing with the values extracted randomly from a Gaussian variable, thus inserting white random fluctuations in the data. But the difference between the two values is small and the spectral behaviour is approximately the same.

After generating modified series with the same spectral properties of the original series and without gaps, we performed the Higuchi fractal analysis. We calculated the lengths of the curve $<L(\tau)>$ vs. the time interval τ in accordance with (2) for each modified series, and then we averaged them. The slope of the line fitting the log–log plot of the average length of the curve $<L(\tau)>$ vs. the time

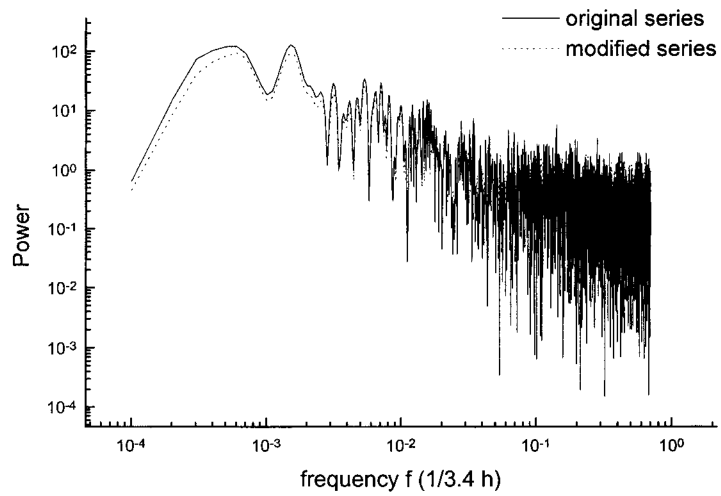

Figure 6. Log–log plot of the power spectrum of the original data (solid line) and the averaged power spectrum of modified series (dotted line). Both the spectra behave as power-law functions of the frequency *f*, with similar values of the spectral indices and Hurst exponents

interval τ (Figure 7) gives the estimate of the fractal dimension, $D = 1.198 \pm 0.002$. From this value we estimated a spectral exponent $\alpha = 1.164 \pm 0.002$, in good accordance with the previous values of the spectral indices, calculated with the Lomb Periodogram.

In order to better characterize the considered time series, the Hurst exponent has been computed from the values of the power law index. This gives an estimate of $Hu = 0.17 \pm 0.06$. This value is significantly lower than 0.5 and indicates that the considered series, despite its marked irregularity, cannot be considered as purely random. In particular, the time series is characterized by a certain degree of predictability in the form of anti-persistent behaviour.

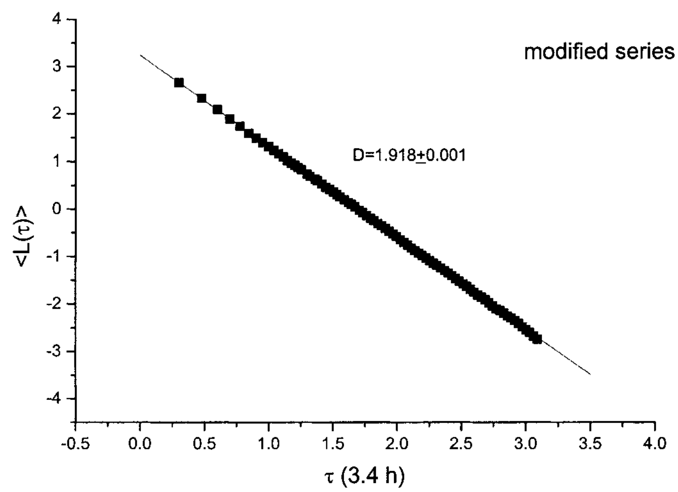

Figure 7. Log–log plot of the average length of the modified time series curve $L(\tau)$ vs. the time interval τ. The fractal dimension D is obtained by the slope of the line fitting the curve. The estimated value of the spectral index is consistent with the estimates obtained by the spectral methods

4. CONCLUSIONS

The time series resulting from 1 year monitoring of ^{222}Rn emissions in the gaseous phase from a bubbling mud volcano in Northern Italy has been analyzed in order to get some insight into the properties of the underlying physical process. The time series obtained after the removal of possible spurious effects induced by local meteoclimatic conditions is characterized by strong irregularity and antipersistence. The fractal dimension of the resulting pattern is of the order of 1.2.

The power spectrum shows a 'power law' pattern which can be considered the 'fingerprint' of a complex dynamical system with a relatively large number of degrees of freedom. This dynamic complexity (probably related to the bubbling process) could supply an interpretation for the apparent lack of sensitivity of the considered system to forcing terms of geodynamic origin such as the earth's tides. This result suggests that ^{222}Rn measurements resulting from the monitoring of bubbling gaseous phases in mud volcanoes are less promising for the study of geodynamical phenomena than those obtained from the liquid phase in the same type of structures.

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