Physica A 391 (2012) 1553–1562

Contents lists available at SciVerse ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Investigating the temporal variation of the scaling behavior in rainfall data measured in central Argentina by means of detrended fluctuation analysis

Luciano Telesca [a,*], Jorge O. Pierini [b], Beatrice Scian [c]

[a] *CNR, Istituto di Metodologie per l'Analisi Ambientale, C.da S.Loja, 85050 Tito (PZ), Italy*

[b] *Universidad Nacional del Sur – Departamento de Física – IFISUR - CCT BB- Comisión de Investigaciones Científicas de la Provincia de Buenos Aires - C.C. 804, Florida 8000 Complejo CCT, B8000FWB Bahía Blanca, Argentina*

[c] *Universidad Nacional del Sur – Departamento de Agronomía – CONICET- B8000FWB Bahía Blanca, Argentina*

ARTICLE INFO

Article history:
Received 22 March 2011
Received in revised form 23 August 2011
Available online 30 August 2011

Keywords:
Detrended fluctuation analysis
Rainfall
Argentina
Climate

ABSTRACT

Investigation of the time variant scaling behavior of six monthly rainfall series recorded in central Argentina from 1860 to 2006 by using detrending fluctuation analysis (DFA) was performed. Changes in precipitation extremes are analyzed for several regions of Argentina using long-term monthly rainfall data (back to 1860) recorded by rain gauges extended for more than 10 latitude-degrees, from subtropical regions until 39° S. A moving window was employed in order to analyze statistical changes. Three different types of time patterns can be distinguished: (i) eastern stations show visible crossovers between persistent and random behavior; (ii) north-western stations are characterized by random behavior approximately at any time and do not present visible crossovers between different types of scaling behaviors; (iii) one station (i.e. Corrientes) shows a peculiar pattern, since it is characterized by several crossovers from persistent to random behavior, indicating a more fluctuating time dynamics without a well defined trend. The obtained results can be interpreted in the context of the climatological conditions of Central Argentina, which is characterized by the continental heat low in the northwest region, by the subtropical rainforest in the eastern provinces and by a transition zone (from maritime to continental regime) fluctuating with the South Atlantic high-pressure cell.

1. Introduction

The most interesting meteorological variable within the study of climatic change at a world scale is temperature because it responds directly to global warming and precipitation [1]. The IPCC Working Group I defines [2] as climate change a variation in the mean state of climate or its variability with statistical significance that persists for an extended period (typically decades or longer). This climatic change can be caused by natural internal processes or external forcing or by persistent anthropogenic changes in the composition of the atmosphere or land use.

A strong positive trend in precipitations during the second half of the 20th century characterized the central zone of Argentina. Considerable climate variability has been reported in this region at various temporal scales, from a decadal-scale enhancement of spring/summer precipitation [3] to inter-annual variability associated with the El Niño–Southern Oscillation (ENSO) phenomenon [4–6]. Other studies related to extreme monthly precipitations in the Pampean Region,

* Corresponding author.
E-mail address: luciano.telesca@imaa.cnr.it (L. Telesca).

0378-4371/$ – see front matter
doi:10.1016/j.physa.2011.08.042

restricted only to events under no-ENSO conditions [7], yielded interesting results over the anomalous large-scale circulation patterns associated particularly with the dry season rainfall extremes (May to September).

One of the most prominent aspects is the increasing trend of precipitation and intense storm frequency [8]. Coastal zones are affected because of the increase in the anticyclone frequency and augmented erosion. Although this process has been occurring for a long time, it has been intensified in the recent years because of the sea level increase, the increment of wave force and inadequate land use near the coast [9].

Another important factor is the intense precipitation taking place even with greater intensity in the central and coastal regions. In fact, between March and April 2003, Argentina faced the worst climate catastrophes in the 21th century in the Santa Fe province [10]. The catastrophe took a toll of 130,000 victims, 30 deaths, 28,000 dwellings destroyed and damages of more than US$ 1500 million. In that event, climatic change impacts, such as the greatest precipitation rates, and the loss of forests and bushes throughout all the Northeast region converged.

Following the report Secretaría de Ambiente y Desarrollo Sustentable de la Nación Argentina (2007), since 1999 deforestation in several provinces has allowed the expansion of soy cultivation in more than 2,000,000 hectares. It is estimated that in the Chaco region, one of the most affected, 4,300,000 hectares will have been deforested by the year 2010 if these practice are continued.

Since the above mentioned zones are affected by the changing climatic conditions, it was deemed necessary to establish the measure of the experimental change values in precipitation extremes.

This work aims at detecting whether there are modifications in the variability of monthly precipitation within a retrospective context for central Argentina. Because of the irregular rainfall regime it is necessary to focus the analysis on the study of precipitation variability for the most extended period of available instrumental records. The analysis will be performed by means of detrended fluctuation analysis (DFA), which is a powerful tool to investigate the dynamics of signals, even affected by trends and nonstationarities. The DFA allows us to detect scaling in observational data, and, thus, the presence of correlated structures in their time variability. The knowledge of the time structure of an observational series is crucial for the general understanding of the inner governing mechanisms, which could be positive feedback for persistent series or negative feedback for antipersistent series [11]. Kurnaz [12] applied the DFA to investigate the power law behavior of the monthly averages of the maximum daily temperatures in different sites in the US, distinguishing different geographical regions with different power law exponents and finding different climatic zones. Suteanu [13] analyzed the daily temperatures recorded in stations from Atlantic Canada over a time interval of more than 100 years, finding stronger persistence for oceanic than for coastal locations, and increase of the scaling exponents with the decrease of the difference between average minimum and maximum temperature, which could be relevant for future climate variability.

2. The detrended fluctuation analysis

Persistent temporal fluctuations in signal variability correspond to the $1/f^{\beta}$-power spectrum, where f is the frequency and the scaling exponent $\beta > 0$. Generally, by using a least square method to fit the spectrum plotted on log–log scales and estimate the scaling coefficient, we are able to obtain quantitative information on the strength of persistent correlations of the signal and to gain insight into the kind of mechanisms that may be responsible of its generation. The strength of these correlations provides useful information about the inherent memory of the system [14–17]. The detrended fluctuation analysis (DFA) [18] avoids spurious detection of correlations that are artifacts of trends and nonstationarity that often affects experimental data. Such trends have to be well distinguished from the intrinsic fluctuations of the system in order to find the correct scaling behavior of the fluctuations. The DFA method was shown to be able to quantify scaling in noisy signals for a wide range of correlations; revealing that there is a competition between a trend and a noise, and that this competition can lead to crossovers in the scaling, which can be explained by the superposition of the separate results of the DFA method on the noise and on the trend, assuming that the noise and the trend are not correlated, and that the scaling properties of the noise and the apparent scaling behavior of the trend are known [19]. Studies on the effects of different types of nonstationarities often encountered in real data (gaps, spikes and outliers, different standard deviations or correlation properties within the same signal) showed the appearance of crossovers in the scaling behavior [20].

The DFA method works as follows. In order to analyze the rainfall time series, we briefly present an introduction to the DFA, which is constituted by the following steps:

(1) Consider the signal $x(i)$, where $i = 1, \ldots, N$, and N is the total number of samples. We integrate the signal $x(i)$ and obtain

$$y(k) = \sum_{i=1}^{k} x(i) - \langle x \rangle, \tag{1}$$

where $\langle x \rangle$ is the mean value of x.

(2) The integrated signal $y(k)$ is divided into boxes of equal length n.

(3) For each n-size box, we fit $y(k)$, using a polynomial $y_n(k)$, which represents the trend in that box.

(4) The integrated signal $y(k)$ is detrended by subtracting the local trend $y_n(k)$ in each box of length n.

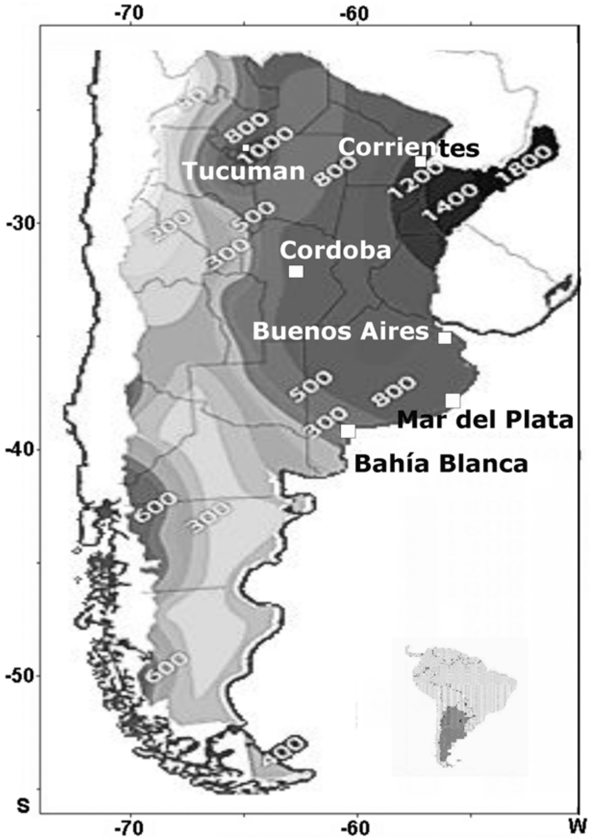

Fig. 1. Map of the rainfall stations and annual mean rainfall.

(5) For a given n-size box, the root-mean-square fluctuation, $F(n)$, for this integrated and detrended signal is given by

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k) - y_n(k)]^2}. \tag{2}$$

(6) The above procedure is repeated for all the available scales (n-size box) to furnish a relationship between $F(n)$ and the box size n, which for long-range power-law correlated signals is a power-law

$$F(n) \sim n^{\alpha}. \tag{3}$$

(7) The scaling exponent α quantifies the strength of the long-range power-law correlations of the signal: if $\alpha = 0.5$, the signal is uncorrelated; if $\alpha > 0.5$ the correlations of the signal are persistent, where persistence means that a large (small) value (compared to the average) is more likely to be followed by a large (small) value; if $\alpha < 0.5$ the correlations of the signal are antipersistent, which indicates that a large (small) value (compared to the average) is more likely to be followed by a small (large) value. The DFA exponent α and the spectral exponent β are related to each other by $\alpha = (1 + \beta)/2$ [21].

3. Data analysis

Rainfall data were obtained from the archives of the National Weather Service (*Servicio Meteorologico Nacional*) and the National Institute of Agricultural Technology (*INTA: Instituto Nacional de Tecnologia Agropecuaria*). The time series were chosen for their record length and reliability of observations, and were checked for missing data before performing the analysis. Only Tucuman and Corrientes presented missing data, which were filled by using a regression method [22]. In particular Tucuman data were compared with Famailla data (from INTA), 35 km apart; while Corrientes data were compared with the data of two close stations (Resistencia and Goya, at about 22 km). However, the amount of missing data is less than 5% of the record length. The monthly rainfall series recorded in central Argentina were: (1) Buenos Aires (BUE) spanning from 1861 to 2006, (2) Bahia Blanca (BHI) spanning from 1860 to 2006, (3) Cordoba (CDB) spanning from 1873 to 2006, (4) Corrientes (COR) spanning from 1876 to 2006, (5) Mar del Plata (MDP) spanning from 1888 to 2006 and (6) Tucuman (TUC) spanning from 1880 to 2006. Fig. 1 shows the mean annual rainfall distribution for the base period 1961–1990 together

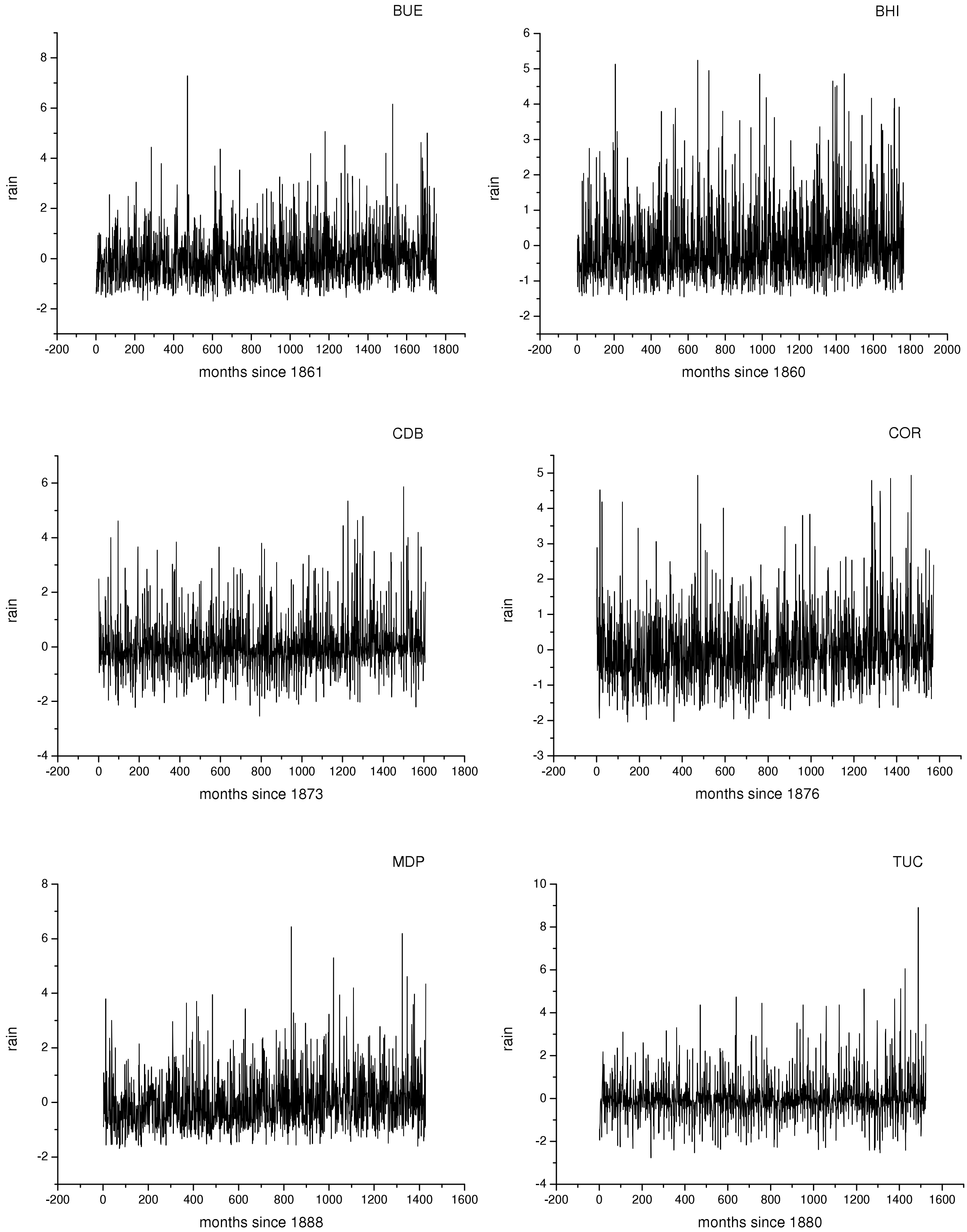

Fig. 2. Rainfall data after removing the seasonal periodicities.

with the geographical location of the rainfall stations, according to the climatic regions of Argentina [23]. Fig. 2 shows the time variation of the rainfall data after removing the seasonal periodicities. The seasonal periodicities were removed by means of a Fourier filtering. The DFA was performed also on the magnitude time series. Similar investigation were performed on air temperature time series by Podobnik et al. [24]. Fig. 3 shows the results of the DFA performed on the rainfall time series

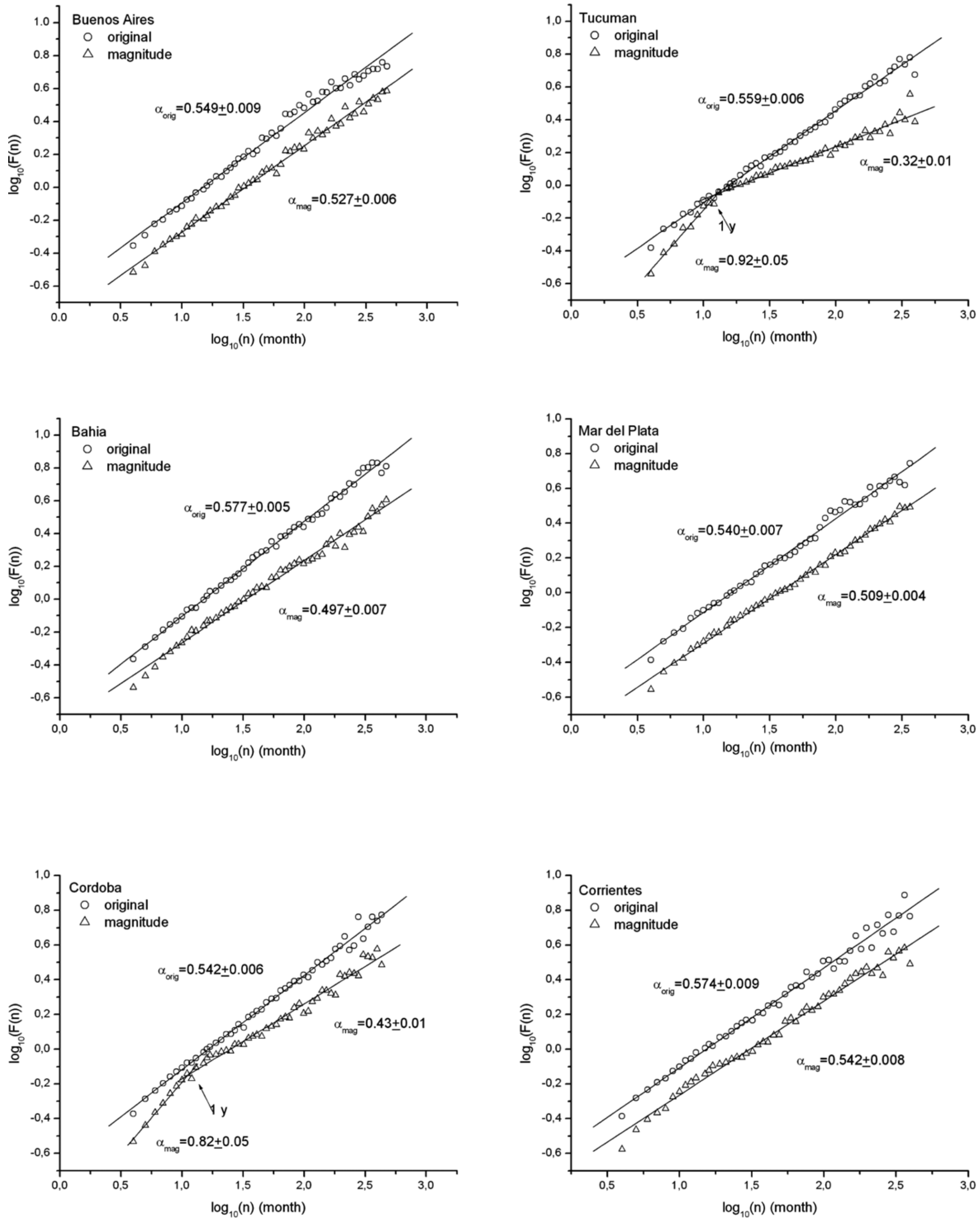

Fig. 3. DFA results for the rainfall time series and their magnitudes.

and their magnitudes. Four stations (BUE, BHI, MDP and COR) show almost similar scaling between the original times series and their magnitudes; but TUC and CDB reveal striking differences in the scaling of the magnitude of the rainfall time series. In particular two scaling regimes are visible with a crossover at about 1 year. The power-law correlations are persistent below this crossover, and antipersistent for timescales larger than 1 year. For TUC and CDB this indicates that on timescales shorter than 1 year, an increase (decrease) of rainfall is followed predominantly by an increase (decrease) of the rainfall; whereas on timescales longer than 1 year an increase (decrease) of rainfall is very likely followed by a decrease (increase) of rainfall.

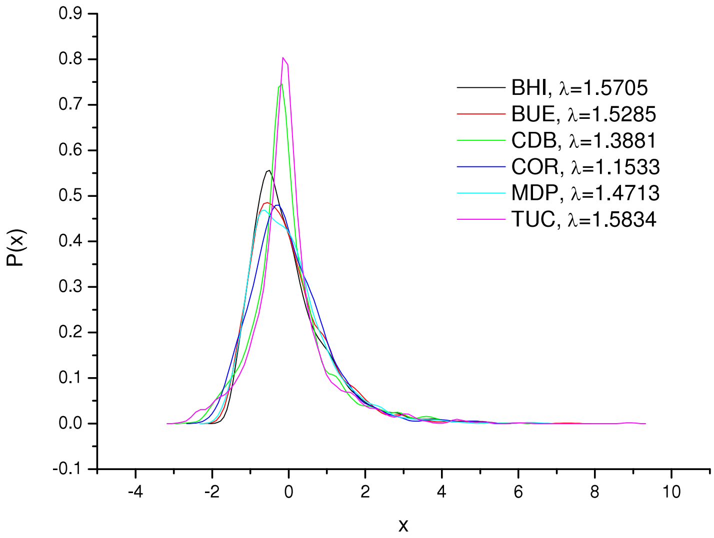

Fig. 4. Probability density functions and skewness of the rainfall time series. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Following Podobnik et al. [25], an analysis of the level of asymmetry was performed on the rainfall time series. Fig. 4 shows the probability distributions of the six monthly rainfall data. It is clearly visible that TUC and CDB are characterized by the presence of the highest peak approximately centered on zero. Although the skewness of all the stations is positive, indicating a right-skew shape of the probability density function, with a relative predominance of values higher than the sample mean, COR has a skewness significantly lower than those of the other stations.

In order to evaluate the cross-correlation between any rainfall series we applied the Detrended Cross-Correlation method (DCCA), which is developed similarly to the DFA. Podobnik et al. [26] used the DCCA to study the effect of periodic trends on systems with power-law cross-correlations. If the two series are cross-correlated the detrended covariance F_{DCCA} scales with the scale n, $F_{\mathrm{DCCA}} \approx n^{\gamma}$, where γ is approximately the average between the scaling exponents of the two series. Generally, if the detrended covariance oscillates around zero, there are no power-law cross-correlations with an unique exponent, but either no cross-correlations or only short range cross-correlations exist between the two series [27–29]. The results of the DCCA reveal that the cross-correlation between two rainfall time series is not characterized by a single power-law behavior, but is more complex, showing the co-existence of more than scaling regime in some cases (see Fig. 5a, as an example) or a "perturbed" single scaling behavior (see Fig. 5b, as an example). These results indicate that the cross-correlation relationship between two rainfall time series are not simply of power-law type.

The evaluation of the time variation of the scaling behavior of rainfall data was carried out using a time window shifting through the series. Each time window selects a subseries of the rainfall data, the DFA was applied to this subseries and, then, the scaling exponent estimated. The scaling exponent was estimated on the timescale range between 4 months and $N_w/4$, where N_w is the length of the time window. Fig. 6 shows the time variation of the scaling exponent α, calculated on a shifting time window of 40 years with a shift of 1 year. Each value was associated with the time of the first rainfall datum in the window. The range of variation of α is quite small, between approximately 0.45 and 0.8 for BUE, but smaller for the other time series. Therefore, in order to evaluate the significance of the obtained values with respect to random behavior, in each plot of Fig. 6 the 5% and 95% confidence curves are also shown. The calculation of the confidence curves proceeded in the following manner. In each window, one thousand shuffles of the selected rainfall subseries were generated. Shuffling destroys as much of the original dynamical structure (i.e. correlations) in a time series as possible, thus making the subseries realizations of white noise characterized by a scaling exponent close to 0.5. Then the DFA was performed on each shuffle of the subseries and the scaling exponent of the shuffle was calculated. The range of scaling values that contain 5% and the 95% of the scaling coefficients of the shuffles for a given time window are respectively the 5% and the 95% confidence curves. Therefore if the scaling exponent of the original subseries (selected by the shifting time window) is higher than the corresponding 95% confidence value, this indicates a significant persistent character of the subseries; if the scaling exponent of the original subseries is lower than the corresponding 5% confidence value, this indicates a significant antipersistent character of the subseries; while if the scaling exponent is within the region delimited by both the confidence curves, then the scaling exponent is not significantly different from that obtained by the random shuffling and thus indicates a random, uncorrelated, white-noise-type behavior.

Three different types of time patterns can be distinguished: (1) TUC and CDB are characterized by random behavior approximately at any time and do not present visible crossovers between different types of scaling behaviors; (2) BUE, BHI and MDP show visible crossovers between persistent and random behaviors. In particular BUE shows a crossover around 1914, BHI at about 1882 and 1917 and MDP at around 1900. It is quite striking that almost concomitantly BUE and BHI change

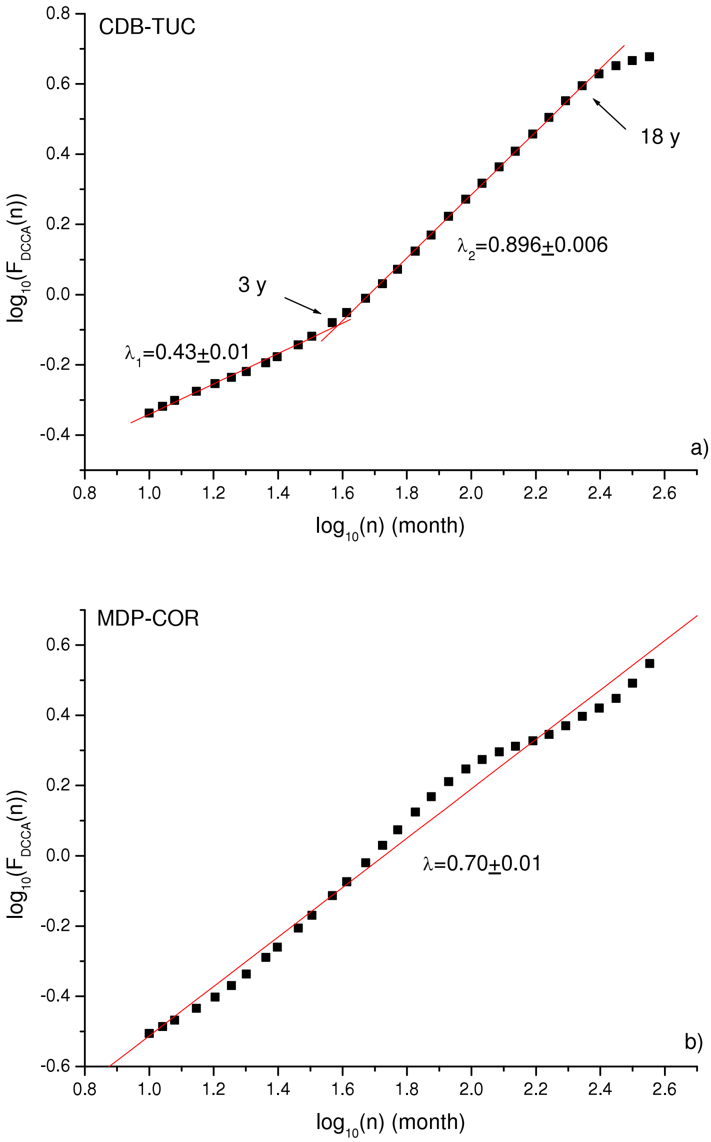

Fig. 5. Examples of the DCCA applied to the rainfall time series.

their dynamics from a persistent to a random behavior. It is also interesting that all three time series are characterized by persistent temporal fluctuations in the early years of measurements (up to 1900–1917), while later their behavior is almost stable characterized by randomness; (3) COR shows a different pattern, because it is characterized by several crossovers, indicating a more changing time dynamics without a well defined trend.

In order to check if the obtained results could be influenced by the choice of the length of the shifting time window, similar analysis was performed using 30-year-long and 50-year-long time windows. The results, shown in Fig. 7, indicate that there is no dependence on the length of the time window.

4. Conclusions

We studied the time variation of the scaling behavior of rainfall monthly data of six sites in Argentina. The results were checked against the randomness and the dependence on the length of the time window. The typical behaviors shown by all the rainfall time series is persistent and/or purely random. Antipersistence does not feature in any of the analysed series. We found that there exist different scaling patterns, which characterize the eastern (Buenos Aires, Bahia Blanca and Mar del Plata) and the north-western stations (Tucuman and Cordoba), showing twofold and single trends respectively; the scaling behavior of the eastern stations changes between persistence and randomness with visible time crossovers, while the north-western stations are almost permanently in a random regime. Corrientes data are, instead, featured by a peculiar pattern,

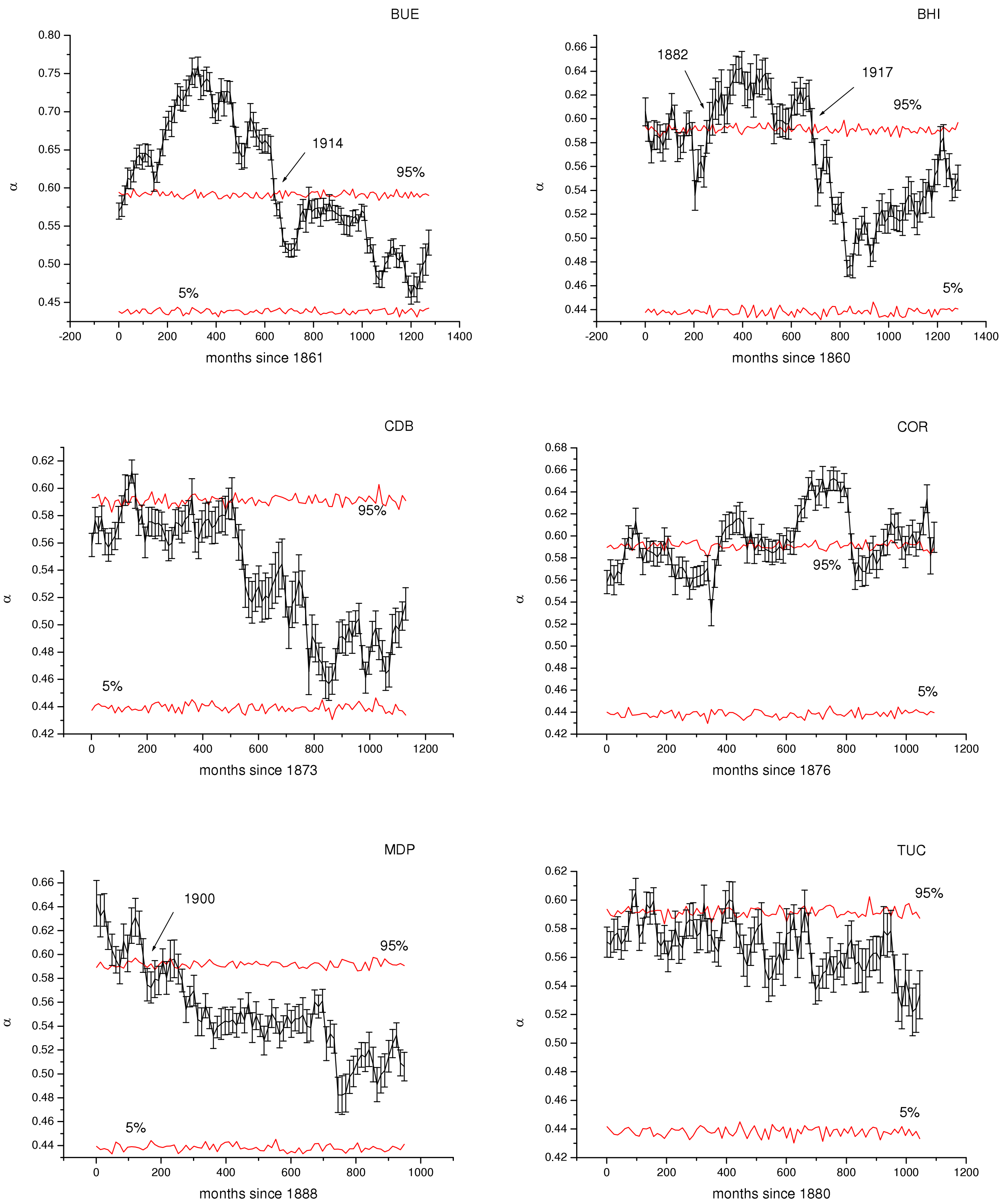

Fig. 6. Time variation of DFA scaling exponent α for the six rainfall data, shown in Fig. 2, using a 40-year long time window and shift of 1 year.

well distinct from the previous ones, since they are characterized by a more fluctuating behavior, indicating a more unstable regime.

Such results can be interpreted, taking into account of the climatological conditions of the Central Argentina, which is well defined by the influence of the Atlantic Ocean. The distance from this source of water vapor defines precipitation regimes of the region. Besides, the continental thermal low located between 20° S and 30° S, over the relative high and dry terrain east of the Andes produces orographic rainfall over the eastern slopes of the "sierras" in Tucuman and extends its effect

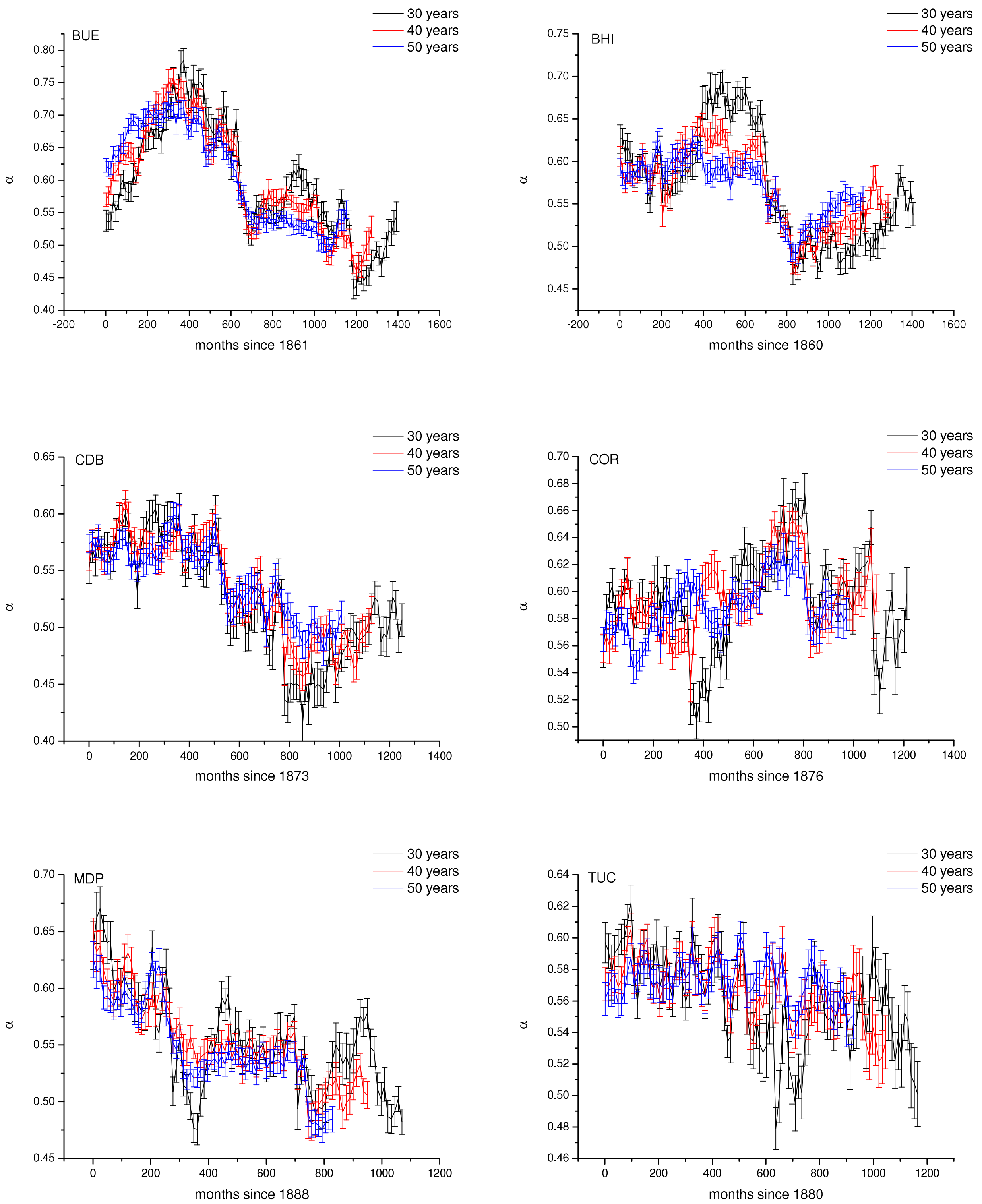

Fig. 7. Comparison of the α-curves for the six rainfall data shown in Fig. 2, using 30-, 40- and 50-year-long time windows. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

further south toward Cordoba [30]. The increase of rainfall to the East exhibits a maritime character and defines a rainforest regime that affects the Mesopotamia provinces, in which Corrientes is located [30]. Mar del Plata, Buenos Aires and Bahia Blanca are located in a transition zone, which lies between humid (maritime) and dry (continental) subtropical regions [31], characterized by a very rapid decrease of vapor pressure from the coast in the direction of the pampas, East to West.

The obtained results indicates how the scaling behavior of the rainfall time series is a good indicator of the climatology of an investigated area and can contribute in deepening the understanding of the complex climatological interactions.

Acknowledgments

The present study was supported by the CNR-CONICET 2011–2012 Project ''Development of models and time series analysis tools for oceanographic parameters analysis and forecasting''.

References

[1] L. Alexander, X. Zhang, T.C. Peterson, J. Caesar, B. Gleason, A. Klein Tank, M. Haylock, D. Collins, B. Trewin, F. Rahimzadeh, A. Tagipour, P. Ambenje, K. Rupa Kumar, J. Revadekar, G. Griffiths, L. Vincent, D. Stephenson, J. Burn, E. Aguilar, M. Brunet, M. Taylor, M. New, P. Zhai, M. Rusticucci, J.L. Vazquez-Aguirre, Global observed changes in daily climate extremes of temperature and precipitation, J. Geophys. Res. 111 (2006) D05109.
[2] IPCC. 2007. Climate change 2007: The physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press: Cambridge, United Kingdom and New York. Working Group II: Impacts, Adaptation and Vulnerability, 19.2: 341–379.
[3] E. Castañeda, V. Barros, Las tendencias de la precipitación en el Cono Sur de América al este de los Andes, Meteorologica 19 (1994) 23–32.
[4] W. Vargas, O.C. Penalba, J.L. Minetti, Las precipitaciones mensuales en zonas de la Argentina y el ENSO. Un enfoque hacia problemas de decisión, Meteorologica 24 (1999) 3–22.
[5] A.M. Grimm, V.R. Barros, M.E. Doyle, Climate variability in southern South America associated with El Niño and La Niña events, J. Clim. 13 (2000) 35–58.
[6] M. Rusticucci, W. Vargas, Cold and warm events over Argentina and their relationships with ENSO phases: risk evaluation analysis, Int. J. Climatol. 22 (2002) 467–483.
[7] B. Scian, J.C. Labraga, W. Reimers, O. Frumento, Characteristics of large-scale atmospheric circulation related to extreme monthly rainfall anomalies in the Pampa Region, Argentina, under non-ENSO conditions, Theor. Appl. Climatol. 85 (2005) 89–106.
[8] V. Barros, A. Menendez, G. Nagy, eds., 2006. El Cambio Climático en el río de la Plata, 107–111, CIMA-CONICET, Buenos Aires.
[9] J.O. Codignotto, Vulnerabilidad al ascenso del nivel del mar y cambio climático en la costa Argentina, Asociación Argentina de Geología Aplicada a la Ingeniería 21 (2005) 25–28.
[10] S.A.C. Doldán, 2004. La catástrophe de Santa Fe. in: Simpósio Brasileiro de Desastres Naturais, 1, 2004, Florianopolis, GEDN/UFSC, 2004, pp. 819–833.
[11] V. Cuomo, M. Lanfredi, V. Lapenna, M. Macchiato, M. Ragosta, L. Telesca, Antipersistent dynamics in short time scale variability of self-potentials, Annali di Geofisica 43 (2000) 271–278.
[12] M.L. Kurnaz, Detrended fluctuation analysis as a statistical tool to monitor the climate, J. Stat. Mech. (2004) P07009. doi:10.1088/1742-5468/2004/07/P07009.
[13] C. Suteanu, Detrended fluctuation analysis of daily atmospheric surface temperature records in Atlantic Canada, The Canad. Geographer 55 (2011) 180–191.
[14] L. Telesca, M. Lovallo, Non-uniform scaling features in central Italy seismicity: a non-linear approach in investigating seismic patterns and detection of possible earthquake precursors, Geophys. Res. Lett. 3 (2009) L01308.
[15] L. Telesca, Cycles, scaling and crossover phenomenon in length of the day LOD time series, Physica A 379 (2007) 459–464.
[16] L. Telesca, M. Lovallo, V. Lapenna, M. Macchiato, Long-range correlations in two-dimensional spatio-temporal seismic fluctuations, Physica A 377 (2007) 279–284.
[17] L. Telesca, G. Colangelo, V. Lapenna, M. Macchiato, Fractal approaches in investigating the time dynamics of self-potential hourly variability, Int. J. Earth Sci. 94 (2005) 285–300.
[18] C.K. Peng, S.V. Buldyrev, S. Havlin, M. Simons, H.E. Stanley, A.L. Goldberger, Mosaic organization of DNA nucleotides, Phys. Rev. E 49 (1994) 1685–1689.
[19] K. Hu, Z. Chen, P.Ch. Ivanov, P. Carpena, H.E. Stanley, Effect of trends on detrended fluctuation analysis, Phys. Rev. E 64 (2001) 011114.
[20] Z. Chen, P.Ch. Ivanov, K. Hu, H.E. Stanley, Effect of nonstationarities on detrended fluctuation analysis, Phys. Rev. E 65 (2002) 041107.
[21] S. Havlin, R. Selinger, M. Schwartz, H.E. Stanley, A. Bunde, Random multiplicative processes and transport in structures with correlated spatial disorder, Phys. Rev. Lett. 61 (1988) 1438–1441.
[22] L.A. Vincent, E. Mekis, 2004. Variations and trends in climate indices for Canada. in: Proceeding of 14th Conference on Applied Climatology, 11–15 January 2004, Seattle, Washington. American Meteorological Society, p. 5.
[23] A.L. Cabrera, 1976. Regiones fitogeográficas argentinas, Enciclopedia Argentina de Agricultura y Jardinería, Tomo II, Fasc I, Ed. Buenos Aires.
[24] B. Podobnik, P.Ch. Ivanov, K. Biljakovic, D. Horvatic, H.E. Stanley, I. Grosse, Fractionally integrated process with power-law correlations in variables and magnitudes, Phys. Rev. E 72 (2005) 026121.
[25] B. Podobnik, P.Ch. Ivanov, V. Jazbinsek, Z. Trontelj, H.E. Stanley, I. Grosse, Power-law correlated processes with asymmetric distributions, Phys. Rev. E 71 (2005) 025104.
[26] B. Podobnik, I. Grosse, D. Horvatic, S. Ilic, P.Ch. Ivanov, H.E. Stanley, Quantifying Cross-Correlations Using Local and Global Detrending Approaches, Eur. Phys. J. B 71 (2009) 243.
[27] B. Podobnik, H.E. Stanley, Detrended cross-correlation analysis: a new method for analyzing two non-stationary time series, Phys. Rev. Lett. 100 (2008) 084102.
[28] B. Podobnik, D. Horvatic, A. Petersen, H.E. Stanley, Cross-correlations between volume change and price change, PNAS 106 (2009) 22079.
[29] D. Horvatic, H.E. Stanley, B. Podobnik, Detrended cross-correlation analysis for non-stationary time series with periodic trends, Europhys. Lett. 94 (2011) 18007.
[30] W. Schwerdtfeger, Climates of Central and South America World Survey Climatology, 12, Elsevier, Ámsterdam, 1976.
[31] F. Prohaska, Las características de las precipitaciones en la región semiárida pampeana, Revista de Investigación Agrícola RIA (2) (1961) 199–232. Bs. As. XV.