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Long-term correlations and cross-correlations in wind speed and solar radiation temporal series from Fernando de Noronha Island, Brazil

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HIGHLIGHTS

- We analyze correlations of simultaneous wind speed and solar radiation data.
- Both processes shows persistent correlations and cross correlations.
- Wind speed demonstrates stronger persistency.
- We find complementarity in persistence of wind speed and solar radiation dynamics.

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ABSTRACT

We analyze correlations and cross-correlations in wind speed and solar radiation temporal series recorded at the Island Fernando de Noronha in northeastern Brazil, using Detrended fluctuation analysis (DFA) and Detrended cross-correlation analysis (DCCA). We find that both processes exhibit persistent long-term power law correlations as well as persistent long term cross correlations. The observed persistency is found to be stronger for wind speed then for solar radiation, as indicated by higher value of the scaling exponent. By applying DFA on sliding windows of 365 day duration, we find that persistency is preserved for these windows along the entire studied period. In the periods when the decrease in correlation exponent for wind speed is observed, solar radiation shows increased persistency (higher values of correlation exponent) indicating the existence of certain complementarity between persistence property of the two stochastic processes.

1. Introduction

Solar and wind energy play a strategic role in Brazil's efforts for sustainable development. Brazil is one of thirteen countries involved in the Solar and Wind Resource Assessment (SWERA) project, designed to provide a reliable database in solar and wind energy resources, together with socio-economic, infrastructure and environmental information, that enable policy makers to evaluate potential for investments in new renewable energy technologies [1]. The implementation of such technologies is meant to facilitate energy supply in remote areas as in the Amazon region and islands, and help reduce greenhouse gases emissions to the atmosphere by reducing the fossil fuel consumption. The high solar irradiation levels with small seasonal variation and trade wind regime make the coastal areas of northeastern Brazil especially attractive

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for alternative energy developing programs [1–3]. The use of solar and wind sources of energy in this region should help regulating energy production during dry season, and preservation of bio environmental resources for future generations.

Fernando de Noronha archipelago, located about 360 km offshore from the Brazilian coast in the Atlantic Ocean, belongs to the state of Pernambuco and is divided in two conservation units: National Marine Reserve (retained for fauna, flora and natural resources protection) and Environmental Protected Area which is reserved for human occupation. Each of these units has preservation rules established by the federal and the state governments with the aim of preservation of natural resources. The first large wind turbine for commercial operation in South America was installed at this location in 1992 [4], and since then there were several attempts to implement wind and solar energy generation at the island. Currently the islands energy supply comes mainly from diesel generators, and there has been a continuous effort in developing efficient technological solutions for energy supply based on integration of wind and solar resources [5]. The success of these efforts requires a better understanding of the behavior of simultaneous wind speed and solar radiation data from this location.

Solar radiation and wind speed temporal dynamics are characterized by high intermittency, due to the dependence on weather and climatic changes, and the variations of solar and wind energy output in general does not match the time distribution of the energy load demand. The independent use of these energy resources cannot provide a continuous power supply for stand-alone systems due to seasonal and periodical variations. This problem may be partially or fully overcome with hybrid solar-wind power generation systems that integrate the two energy resources using their complementary characteristics. This solution improves system efficiency and reliability of the energy supply and reduces the energy storage requirements compared to systems comprising only one single renewable energy source [6,7]. Traditionally, classical statistical methods were used to evaluate wind and solar radiation potential for energy generation [1,2,8–10] but recently developed methods from complex system science should provide complementary information about the nature of underlying stochastic processes governing wind speed and solar radiation variability, which is crucial for development and evaluation of reliable theoretical and computational prediction models [11–20].

In order to contribute to a better understanding of wind speed and solar radiation temporal variability at the location of Fernando de Noronha Island, which provides the base for evaluation of renewable energy potential at this location, in this work we analyze long-term correlations and cross-correlations in daily wind speed and solar radiation temporal series registered during the period 2004–2013. We use Detrended fluctuation analysis (DFA) method [21] and Detrended cross-correlation (DCCA) method [22], which were designed to quantify correlations and cross-correlations in non-stationary signals. In the following section we describe data and methodology, in the subsequent section we present the results and discussion of our analysis, and finally we draw the conclusions.

2. Data and methodology

2.1. Data

The data used in this work are part of a historical climatic database [23] provided by the Center for Time Prevision and Climatic Studies (Centro de Previsão de Tempo e Estudos Climáticos—CPTEC) of the Brazilian National Institute for Space Research (Instituto Nacional de Pesquisas Espaciais—INPE). We chose daily wind speed and solar radiation data recorded at Fernando de Noronha Island located in the Atlantic ocean east of the state Rio Grande do Norte, Brazil (longitude: 32, 41 W; latitude: 3, 84 S; altitude: 38 m), during the period 07/08/2004–12/21/2013 with 3295 observations for each variable.

The raw time series for average daily wind speed and accumulated daily solar radiation are presented in Fig. 1.

In order to make sure that seasonality does not affect the temporal correlation analysis, we first normalize the original series $x(t)$ by calculating

$$X(t) = \frac{x(t) - \langle x(t)\rangle_d}{\sigma_d}, \tag{1}$$

where $\langle x(t)\rangle_d$ is the mean of the observed quantity (wind speed, or solar radiation) calculated for each calendar date d (obtained by averaging over all the years in the record), and σ_d is the corresponding standard deviation (also calculated for each calendar date).

2.2. Detrended fluctuation analysis

To quantify and compare correlations in wind speed and solar radiation time series we use Detrended fluctuation analysis (DFA) introduced by Peng et al. [21] for linear detrending, and extended to higher older polynomials by Kantelhardt et al. [24] and Hu et al. [25]. This method is suitable to quantify long-term correlations in non-stationary signals [25,26] and has been successfully applied on physiological processes [27,28], weather records [15,29], geophysics [30–32] financial data [33,34], and even music [35]. The DFA procedure is briefly described as follows. The original temporal series $x(i),\ i = 1, \ldots, N$ is integrated to produce $y(k) = \sum_{i=1}^{k}[x(i) - \langle x\rangle],\ k = 1, \ldots, N$, where $\langle x\rangle = \frac{1}{N}\sum_{i=1}^{N} x(i)$ is the average. Next, the integrated series $y(k)$ is divided into N_n non-overlapping segments of length n and in each segment $s = 1, \ldots, N_n$ the linear (or higher order polynomial) least square fit (representing local trend) is estimated. The integrated series $y(k)$ is then detrended by subtracting the local trend $y_{n,s}(k)$ (ordinates of straight line or higher order polynomial fit) from the data in each segment

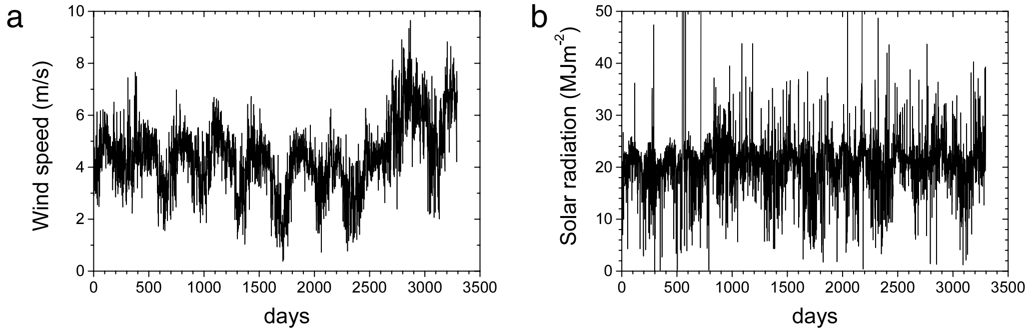

Fig. 1. The average daily wind speed (a) and daily accumulated solar radiation (b) data from Fernando de Noronha.

and detrended variance is calculated as

$$F_{DFA}^2(n) = \frac{1}{nN_n} \sum_{s=1}^{N_n} \sum_{k=n(s-1)+1}^{ns} [y(k) - y_{n,s}(k)]^2. \tag{2}$$

Repeating this calculation for different box sizes provides the relationship between fluctuation function $F_{DFA}(n)$ and box size n, where typically $F_{DFA}(n)$ increases with n according to a power law $F_{DFA}(n) \sim n^{\alpha}$. The scaling exponent α is obtained as the slope of the regression (least square line fitting) of $\log[F_{DFA}(n)]$ versus $\log n$.

The value of $\alpha = 0.5$ indicates an uncorrelated signal (white noise), $\alpha > 0.5$ indicates persistent long-term correlations, $\alpha < 0.5$ indicates anti persistent long-term correlations. The values $\alpha = 1$ and $\alpha = 1.5$ correspond to $1/f$ noise and Brownian noise (integration of white noise) respectively.

2.3. Detrended cross-correlation analysis

Detrended cross-correlation analysis (DCCA) was recently introduced by Podobnik and Stanley [22], and is designed to analyze power-law cross-correlations between two simultaneously recorded non-stationary time series. It has been subsequently extensively studied [36–38], and it has been successfully applied in the analysis of climatic [39], and financial data [33,40,41]. It proceeds as follows: two simultaneously recorded time series $x(i)$ and $y(i)$, $i = 1, \dots, N$ are integrated to produce $X(k) = \sum_{i=1}^{k} x(i)$ and $Y(k) = \sum_{i=1}^{k} y(i)$, where k is an integer between 1 and N. Next, the integrated series are divided into N_n segments of equal length n and a linear (or higher order polynomial) regression is performed for each segment to capture the local trend. The integrated series $X(k)$ and $Y(k)$ are detrended by subtracting the local trends $X_{n,s}(k)$ and $Y_{n,s}(k)$ (ordinates of the straight line or polynomials within each segment $s = 1, \dots, N_n$) from the data in each box, and the detrended covariance is calculated as

$$F_{DCCA}^2(n) = \frac{1}{nN_n} \sum_{s=1}^{N_n} \sum_{k=n(s-1)+1}^{ns} [X(k) - X_{n,s}(k)][Y(k) - Y_{n,s}(k)]. \tag{3}$$

Repeating this calculation for all segment sizes provides the relationship between $F_{DCCA}(n)$ and the segment size n. If the series are power-law cross-correlated, then $F_{DCCA}(n) \sim n^{\lambda}$ and the scaling exponent λ is determined from the linear regression of $\log[F_{DCCA}(n)]$ versus $\log n$. The interpretation of λ is similar to that of the DFA exponent α. Long-term cross-correlations between two series imply that each series has long memory of its previous values, as well as a long memory of the previous values of the other series [22].

3. Results and discussion

In order to verify whether there exist some linear external trends, and whether linear DFA or higher order polynomial regression should be used, in Fig. 2 we present the results of the DFA1, DFA2 and DFA3 analyses of the wind speed and solar radiation data. It is seen from Fig. 2 that the slope of the regression line is practically the same for all the three cases (difference between the linear and higher order DFA may be attributed to increased fluctuations for large segment size n, rather than some external linear trend), and we therefore continue with the first order DFA and DCCA analyses in the remainder of this paper.

The results of the DFA analysis for original and shuffled wind speed and solar radiation data are displayed in Fig. 3, where it is seen that both wind speed and solar radiation dynamics show persistent properties ($\alpha > 0.5$) with stronger persistency for wind speed indicated by the higher value of scaling exponent. The DFA analysis of shuffled data displays linear behavior with slope very close to 0.5, indicating that the observed power law behavior in the wind speed and solar radiation data stems from the temporal ordering of the observations and associated long-term correlations.

We also apply the DFA analysis to consecutive 365 day windows (with a single-day step) of the wind speed and solar radiation data, to study temporal evolution of the scaling exponents [42]. The variation of the DFA exponents is presented

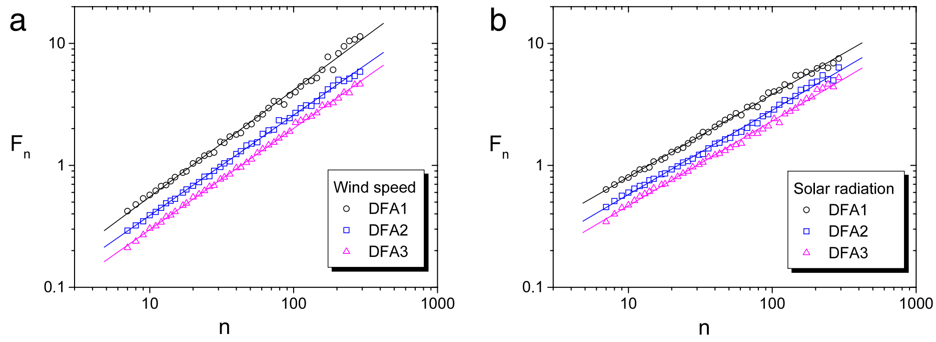

Fig. 2. DFA analysis of order 1, 2 and 3, of the normalized data for (a) average daily wind speed ($\alpha_1 = 0.87 \pm 0.02$, $\alpha_2 = 0.82 \pm 0.01$, $\alpha_3 = 0.83 \pm 0.01$) and (b) accumulated daily solar radiation ($\alpha_1 = 0.68 \pm 0.01$, $\alpha_2 = 0.69 \pm 0.01$, $\alpha_3 = 0.70 \pm 0.01$), from Fernando de Noronha island.

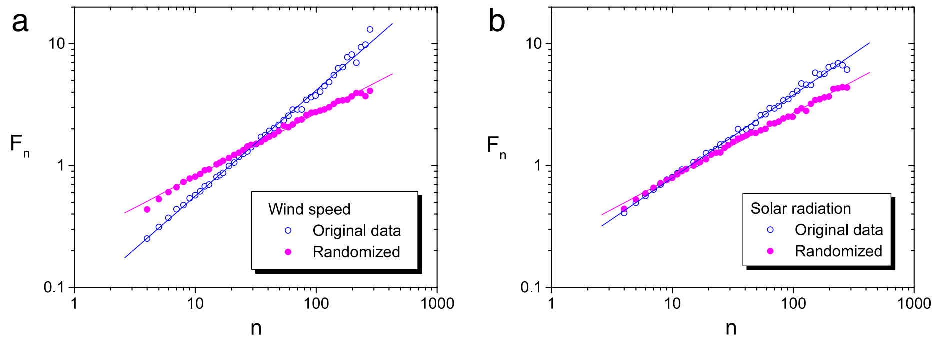

Fig. 3. DFA analysis for the original and shuffled data for (a) the average daily wind speed ($\alpha = 0.87 \pm 0.02$, $\alpha_{rand} = 0.52 \pm 0.01$), and (b) for the accumulated daily solar radiation ($\alpha = 0.68 \pm 0.01$, $\alpha_{rand} = 0.53 \pm 0.01$), from Fernando de Noronha island.

in Fig. 4, where it is seen that for wind speed the power law correlations are preserved during the entire analyzed period, while in the case of solar radiation there are ranges of windows characterized by absence of long-term correlations (when the value of scaling exponent becomes close to 0.5). It is also seen that wind speed shows stronger persistence as compared with solar radiation for almost the entire series, except for years 2005 and 2009, when the values of two scaling exponents become close. The graphs presented in Fig. 4 reveal the periodicity in temporal evolution of scaling exponents, (with period of approximately 5 years) and indicate the complementarity between observed persistence properties: when the scaling exponent for wind speed increases, the scaling exponent of solar radiation decreases, and vice versa. The complementarity between temporal variation of wind and solar energy potential has recently attracted considerable attention with the goal of attaining more efficient use of renewable energy [43–46], as a higher degree of complementarity between their outputs indicates the increased reliability in energy generation in hybrid systems. Our results demonstrate the existence of complementarity between long term correlation properties (measured by the value of DFA exponent), which can be useful in planning of long term use of hybrid systems at this site.

We also apply Detrended cross-correlation analysis (DCCA) on wind speed and solar radiation temporal series to study long term cross-correlations. It was shown recently [47] that the relationship between DFA exponents α_1 and α_2 of two auto-correlated series, and the corresponding DCCA exponent λ, may be established using the cross-correlation coefficient

$$\rho_{DCCA}(n) = \frac{F^2_{DCCA}(n)}{F_{DFA1}(n)F_{DFA2}(n)}. \tag{4}$$

If the two series are not cross-correlated $\rho_{DCCA}(n)$ oscillates about zero (bounded between −1 and 1), for anti cross-correlated series $\rho_{DCCA}(n)$ is negative, and for positively cross-correlated series $\rho_{DCCA}(n) \sim n^{\omega}$, such that

$$\omega = 2\lambda - \alpha_1 - \alpha_2. \tag{5}$$

It turns out that due to canceling out of positive and negative terms (individual series fluctuation products) in (3) both F_{DCCA} and ρ_{DCCA} show very large fluctuations for our data. To remedy this situation we use the sliding window version of the DCCA procedure, where fluctuations are calculated for windows of width n, sliding over the series with unit stride. The results of DCCA analysis together with the DFA graphs of individual series and the cross-correlation coefficient are presented in Fig. 5, where it is seen that daily wind speed and solar radiation temporal series also exhibit positive long-term cross-correlations. The value of cross-correlation exponent $\lambda = 1.05 \pm 0.01$ is related with the average of DFA exponents for individual series $\alpha_{wind} = 0.89 \pm 0.01$ and $\alpha_{rad} = 0.68 \pm 0.01$, and the cross-correlation coefficient $\omega = 0.53 \pm 0.02$ through relation $\lambda = (\omega + \lambda_{wind} + \lambda_{rad})/2$, as predicted in Ref. [47].

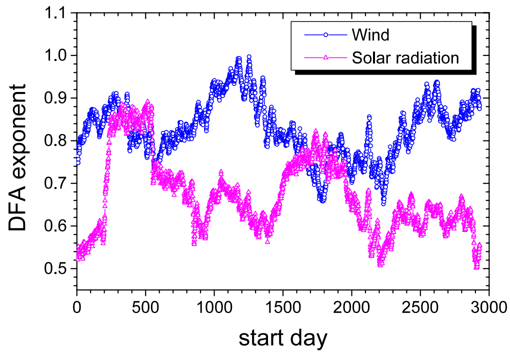

Fig. 4. Temporal variation of DFA exponent for wind speed and solar radiation data from Fernando de Noronha island. The size of the symbols roughly corresponds to the error bars.

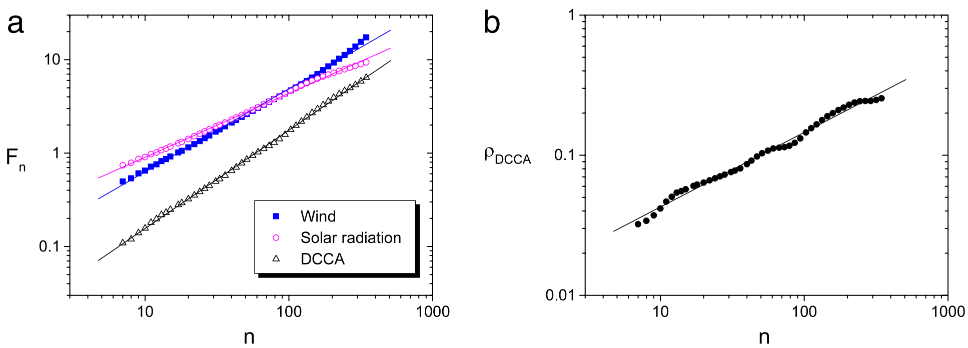

Fig. 5. DCCA analysis for average daily wind speed and daily accumulated solar radiation data from Fernando de Noronha. In (a) the dependence on the window size n of the square root of detrended variance for the two series and the detrended co-variance among the series is shown, with regression line slopes $\alpha_{wind} = 0.89 \pm 0.01$, $\alpha_{rad} = 0.68 \pm 0.01$ and $\lambda = 1.05 \pm 0.01$, respectively, while in (b) the cross-correlation coefficient (4) is presented, with regression line slope $\omega = 0.53 \pm 0.02$.

The existence of long-term correlations in wind speed has been analyzed using fractal [13–15] and multifractal [16–19] approach, while solar radiation records have been receiving less attention [11,12]. The results of these studies using DFA analysis generally agree with our results. On the other hand, to the best of our knowledge there have been no reports on simultaneous wind speed and solar radiation records, and the current work presents the first study of long term correlations *and cross-correlations* in simultaneous wind speed and solar radiation records from the same site, where both solar and wind energy potential is considered viable for energy generation. Our findings suggest that a combination of wind and solar radiation propelled plants should be viable as renewable energy sources for the location of Fernando Noronha Island, due to the persistence and complementarity in the dynamics of these phenomena.

4. Conclusion

In this work we analyze long-term correlations in wind speed and solar radiation temporal series recorded at the location of Fernando de Noronha Island. Both processes are characterized by persistent long memory, with stronger persistency of wind speed data. This property is preserved for 365 day sliding windows, along the entire studied period, however, with varying exponent values. In the periods when the decrease in correlation exponent for wind speed is observed, solar radiation shows increased persistency (higher values of correlation exponent), indicating the existence of a certain level of complementarity between persistence property of the two stochastic processes.

The cross correlation analysis indicates that the wind data are correlated both with wind speed and solar radiation values that occurred in previous periods, and the solar radiation values are also correlated with the previous wind speed and solar radiation data. This correlation may be attributed to a complex relationship cycle: solar radiation affects the wind formation through land, ocean and air heating, producing a pressure gradient and convective air motion, wind in turn affects cloud coverage, and clouds affect solar radiation measurements. What is perhaps the most surprising is that these mutual correlations seem to persist on a yearly scale, and more complete understanding would require additional analysis of other parameters, such as temperature value and gradient over a wider surrounding region, humidity, air pressure and possibly other relevant environmental factors.

Our results provide a new insight to solar radiation and wind speed temporal variability, and should be taken in consideration when planning long term renewable energy generation in Fernando Noronha from individual and hybrid systems that guarantee sustainable development of this island. Future studies including records from different locations (and at different temporal scales) should give more information about observed complementarity in persistent properties between wind speed and solar radiation dynamics.

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References

[1] F.R. Martins, E.B. Pereira, S.L. Abreu, Satellite-derived solar resource maps for Brazil under SWERA project, Sol. Energy 81 (2007) 517–528.
[2] C. Tiba, N. Fraidenraich, H. Grossi Gallegos, F.J.M. Lyra, Solar energy resource assessment—Brazil, Renew. Energy 27 (2002) 383–400.
[3] R.M. Dutra, A.S. Szklo, Incentive policies for promoting wind power production in Brazil: Scenarios for the Alternative Energy Sources Incentive Program (PROINFA) under the New Brazilian electric power sector regulation, Renew. Energy 33 (2008) 65–76.
[4] M.S.M. de Araújo, M.A.V. de Freitas, Acceptance of renewable energy innovation in Brazil—case study of wind energy, Renewable Sustainable Energy Rev. 12 (2008) 584–591.
[5] P. Rosas, C. Studzinski, V. Simoni, F. Neves, A. Fernandes, F.B.L.H.A. Medeiros, G. Azevedo, F. Guimaraes, J. Lima, A. Victor, L. Cabral, J. Arimateia, C. Soares, Developing a supervisory controller for hybrid power system: Fernando de Noronha Island case, Renew. Energy Power Qual. J. (RE&PQJ) 11 (2013) 558–560.
[6] W. Zhou, C. Lou, Z. Li, L. Lu, H. Yang, Current status of research on optimum sizing of stand-alone hybrid solar-wind power generation systems, Appl. Energy 87 (2010) 380–389.
[7] P. Nema, R. Nema, S. Rangnekar, A current and future state of art development of hybrid energy system using wind and PV-solar: A review, Renewable Sustainable Energy Rev. 13 (2009) 2096–2103.
[8] P. Kiss, I.M. Jánosi, Comprehensive empirical analysis of ERA—40 surface wind speed distribution over Europe, Energy Convers. Manage. 49 (2008) 2142–2151.
[9] L. de Araujo Lima, C.R. Bezerra Filho, Wind energy assessment and wind farm simulation in Triunfo–Pernambuco, Brazil, Renew. Energy 35 (2010) 2705–2713.
[10] C.A. Gueymard, S.M. Wilcox, Assessment of spatial and temporal variability in the US solar resource from radiometric measurements and predictions from models using ground-based or satellite data, Sol. Energy 85 (2011) 1068–1084.
[11] S. Harrouni, A. Guessoum, Using fractal dimension to quantify long-range persistence in global solar radiation, Chaos Solitons Fractals 41 (2009) 1520–1530.
[12] R. Calif, F.G. Schmitt, Y. Huang, T. Soubdhan, Intermittency study of high frequency global solar radiation sequences under a tropical climate, Sol. Energy 98 (2013) 349–365.
[13] K. Koçak, Examination of persistence properties of wind speed records using detrended fluctuation analysis, Energy 34 (2009) 1980–1985.
[14] R.G. Kavasseri, R. Nagarajan, Evidence of crossover phenomena in wind-speed data, IEEE Trans. Circuits Syst. I 51 (2004) 2255–2262.
[15] M.S. de Oliveira Santos, T. Stosic, B.D. Stosic, Long-term correlations in hourly wind speed records in Pernambuco, Brazil, Physica A 391 (2012) 1546–1552.
[16] R. Govindan, H. Kantz, Long-term correlations and multifractality in surface wind speed, Europhys. Lett. 68 (2004) 184.
[17] R.G. Kavasseri, R. Nagarajan, A multifractal description of wind speed records, Chaos Solitons Fractals 24 (2005) 165–173.
[18] L. Telesca, M. Lovallo, Analysis of the time dynamics in wind records by means of multifractal detrended fluctuation analysis and the Fisher–Shannon information plane, J. Stat. Mech. Theory Exp. 2011 (2011) P07001.
[19] T. Feng, Z. Fu, X. Deng, J. Mao, A brief description to different multi-fractal behaviors of daily wind speed records over China, Phys. Lett. A 373 (2009) 4134–4141.
[20] L. Telseca, M. Lovallo, Fisher–Shannon analysis of wind records, Int. J. Energy Stat. 01 (2013) 281–290.
[21] 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.
[22] 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.
[23] CPTEC, http://sinda.crn2.inpe.br/PCD/ 2014.
[24] J.W. Kantelhardt, E. Koscielny-Bunde, H.H. Rego, S. Havlin, A. Bunde, Detecting long-range correlations with detrended fluctuation analysis, Physica A 295 (2001) 441–454.
[25] K. Hu, P.C. Ivanov, Z. Chen, P. Carpena, H.E. Stanley, Effect of trends on detrended fluctuation analysis, Phys. Rev. E 64 (2001) 011114.
[26] Z. Chen, P.C. Ivanov, K. Hu, H.E. Stanley, Effect of nonstationarities on detrended fluctuation analysis, Phys. Rev. E 65 (2002) 041107.
[27] A. Bunde, S. Havlin, J.W. Kantelhardt, T. Penzel, J.-H. Peter, K. Voigt, Correlated and uncorrelated regions in heart-rate fluctuations during sleep, Phys. Rev. Lett. 85 (2000) 3736–3739.
[28] R.S. Do Nascimento, L.H.G. de Araujo, R.B. Moraes, C.T. Barbosa, R.C. Guedes, R.A. Nogueira, T. Stošić, Analysis of signal fluctuations of cortical spreading depression: Preliminary findings, Physica A 389 (2010) 1869–1873.
[29] A. Király, I.M. Jánosi, Detrended fluctuation analysis of daily temperature records: geographic dependence over Australia, Meteorol. Atmos. Phys. 88 (2005) 119–128.
[30] L. Telesca, V. Cuomo, V. Lapenna, M. Macchiato, Detrended fluctuation analysis of the spatial variability of the temporal distribution of Southern California seismicity, Chaos Solitons Fractals 21 (2004) 335–342.
[31] L. Telesca, M. Lovallo, V. Lapenna, M. Macchiato, Long-range correlations in two-dimensional spatio-temporal seismic fluctuations, Physica A 377 (2007) 279–284.
[32] L. Telesca, V. Lapenna, M. Macchiato, K. Hattori, Investigating non-uniform scaling behavior in ultra low frequency (ULF) earthquake-related geomagnetic signals, Earth Planet. Sci. Lett. 268 (2008) 219–224.
[33] E.L. Siqueira Jr., T. Stosic, L. Bejan, B. Stosic, Correlations and cross-correlations in the Brazilian agrarian commodities and stocks, Physica A 389 (2010) 2739–2743.
[34] F. Wang, S.J. Shieh, S. Havlin, H.E. Stanley, Statistical analysis of the overnight and daytime return, Phys. Rev. E 79 (2009) 056109.
[35] L. Telesca, M. Lovallo, Revealing competitive behaviours in music by means of the multifractal detrended fluctuation analysis: Application to Bach's Sinfonias, Proc. R. Soc. A: Math. Phys. Eng. Sci. 467 (2011) 3022–3032.
[36] B. Podobnik, D. Wang, D. Horvatic, I. Grosse, H.E. Stanley, Time-lag cross-correlations in collective phenomena, Europhys. Lett. 90 (2010) 68001.
[37] B. Podobnik, Z.-Q. Jiang, W.-X. Zhou, H.E. Stanley, Statistical tests for power-law cross-correlated processes, Phys. Rev. E 84 (2011) 066118.
[38] Z.-Q. Jiang, W.-X. Zhou, Multifractal detrending moving-average cross-correlation analysis, Phys. Rev. E 84 (2011) 016106.
[39] R. Vassoler, G. Zebende, DCCA cross-correlation coefficient apply in time series of air temperature and air relative humidity, Physica A 391 (2012) 2438–2443.
[40] B. Podobnik, D. Horvatic, A.M. Petersen, H.E. Stanley, Cross-correlations between volume change and price change, Proc. Natl. Acad. Sci. USA 106 (2009) 22079–22084.

[41] I. Gvozdanovic, B. Podobnik, D. Wang, H. Eugene Stanley, $1/f$ behavior in cross-correlations between absolute returns in a US market, Physica A 391 (2012) 2860–2866.
[42] A. Carbone, G. Castelli, H. Stanley, Time-dependent Hurst exponent in financial time series, Physica A 344 (2004) 267–271.
[43] C.E. Hoicka, I.H. Rowlands, Solar and wind resource complementarity: Advancing options for renewable electricity integration in Ontario, Canada, Renew. Energy 36 (2011) 97–107.
[44] F. Monforti, T. Huld, K. Bódis, L. Vitali, M. D'Isidoro, R. Lacal-Arántegui, Assessing complementarity of wind and solar resources for energy production in Italy. A Monte Carlo approach, Renew. Energy 63 (2014) 576–586.
[45] S. Jerez, R.M. Trigo, A. Sarsa, R. Lorente-Plazas, D. Pozo-Vázquez, J.P. Montávez, Spatio-temporal complementarity between solar and wind power in the Iberian Peninsula, Energy Procedia 40 (2013) 48–57.
[46] W. Li, S. Stadler, R. Ramakumar, Modeling and assessment of wind and insolation resources with a focus on their complementary nature: A case study of Oklahoma, Ann. Assoc. Amer. Geogr. 101 (2011) 717–729.
[47] G. Zebende, M. da Silva, A.M. Filho, {DCCA} cross-correlation coefficient differentiation: theoretical and practical approaches, Physica A 392 (2013) 1756–1761.