Physica A 392 (2013) 6367–6374

Contents lists available at ScienceDirect

Physica A

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

Multifractal behavior of wild-land and forest fire time series in Brazil

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HIGHLIGHTS

- Hot pixels observed in Brazil between 1998 and 2006 show multifractal behavior.
- The number of hot pixels increases after 2002, accompanied with complexity decrease.
- These findings should be relevant for devising future ecological models for Brazil.

ARTICLE INFO

Article history:
Received 30 March 2013
Received in revised form 25 July 2013
Available online 19 August 2013

Keywords:
Forest fires
Hotspots
Power law
Multifractal detrended fluctuation analysis

ABSTRACT

We examine statistical properties of a daily hot pixel time series recorded in Brazil during the period 1998–2006, using Multifractal Detrended Fluctuation Analysis (MF-DFA). We find that generalized scaling exponent $h(q)$ is a decreasing function of q, indicating multifractal behavior of hot pixel dynamics. We also calculate multifractal spectra $f(\alpha)$ and use fourth-degree polynomial regression to estimate complexity parameters that describe the degree of multifractality of the underlying process. After July 2002, when a significant increase of the number of hot pixel observations is recorded, the complexity of the series is reduced (manifested by the reduction of width of the $f(\alpha)$ spectrum), while small fluctuations increase their dominance over large scale fluctuations (manifested by the increase of skew parameter r). These results should be taken into account when devising ecological and climatic models for Brazil, that contemplate the phenomena of wild-land and forest fires.

1. Introduction

Vegetation fires occur in various ecosystems both as natural events, and as the result of anthropogenic activity. The steady increase of their frequency observed over the past decades increases environmental degradation such as soil erosion, destruction of vegetation cover, loss of biodiversity, changes in landscape patterns and hydrological cycle [1–4]. Vegetation fires also release black and organic carbon and greenhouse gases, which are important factors for global warming [5,6]. Various natural and anthropogenic factors (such as vegetation cover, climatic conditions, topography and fire fighting methods) affect the process of initiation, propagation and suppression of fires, which turns modeling of this phenomenon an extremely difficult task. Consequently, there is an increasing ongoing scientific effort in development of adequate theoretical

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http://dx.doi.org/10.1016/j.physa.2013.08.012

and computational models of fire behavior, which is crucial for understanding and modeling of fire-related phenomena in different ecosystems, and establishing new methods for efficient management of bio-environmental resources, land use, and agriculture [7]. In order to include the effects of vegetation fires in global ecological and climatic models, it is necessary to better understand long-term records of global fire activity, which implies access to consistent global datasets with accurate information about temporal variation and spatial distribution of fires. On the other hand, while fire databases are available for some countries such as USA and Canada, such information is not available for most of the developing countries, and the worldwide historical records are out of reach [8]. Over the past decade there have been various efforts to construct datasets using data from Earth observing satellites [8–11], where satellite sensors register so-called hot pixels with infrared intensity corresponding to burning vegetation. Hot pixels may be considered a strong representative of actual fires, and can be used as a proxy to study spatial and temporal patterns of fire activity, and its relation with climatic and anthropogenic factors [12,13].

Fire records have traditionally been analyzed only using classical statistics [14,15], but recently it was recognized that novel methods for characterizing complex systems can provide important information about the nature of underlying mechanisms that govern fire temporal and spatial variability. In particular, several empirical studies based on forest and wild-land fire archives from different countries have shown that the frequency-burned area distribution displays power-law behavior, for different geographic locations, climatic conditions and types of vegetation [16–20]. This places forest and wild-land fires in the class of phenomena that exhibit self-organized criticality (SOC), characteristic of non equilibrium systems driven by persistent, slow energy input. The term "self-organized criticality" stems from the tendency of these systems maintain the dynamic equilibrium by releasing energy in bursts without a typical size [21]. Other natural hazards such as earthquakes, landslides, snow avalanches and rainfall, have been shown to belong to the same class of physical systems [22–24], and simple cellular automata models have been proposed to explain some of these phenomena: forest fire model for forest and wild-land fires [25,26], sliding block model for earthquakes [27], sand pile model for landslides [28] and Abelian model for rainfall [29]. Recent results that reveal temporal and spatial clustering tendencies within forest fire sequences, long-term correlations between the events and their relation with weather and vegetation parameters, offer additional insight to this extremely complex phenomenon [30–41].

In order to contribute to a better insight into the vegetation fire temporal behavior, in a recent work [42] we have analyzed long-term correlations in daily time series of hot-pixels detected in Brazil by various satellites along the period 1998–2006, using Detrended Fluctuation Analysis. It was found [42] that the observed two regime power-law behavior is rather persistent along the observed period, independent of meteo-climatic variations and the fact that the intensity of the observed hot spot activity has substantially increased since 2002 (related with agricultural expansion — increased soybean plantation area driven by high prices of soybean export, and extreme climatic conditions as severe droughts in Amazon in 2003 and 2005 [43]).

As a continuation of this previous work [42] and motivated by recent result of Telesca and Song [39] that reveals multifractal properties of city fire sequences in China, we apply here the Multifractal Detrended Fluctuation Analysis (MF-DFA) on daily hot pixel data detected in Brazil by the satellite NOAA-12 (National Oceanic and Atmospheric Administration) during the period 1998–2006 with roughly 1.5 million individual hot-pixels observations. As the multifractal behavior of the series is indeed confirmed, we also apply the MF-DFA analysis on the shuffled series to identify the effects of long term correlations and of the power law distribution. We also perform MF-DFA analysis for the periods before and after 2002, where a substantial change of the multifractal spectrum is observed, in contrast with the previous DFA study [42] that showed no difference between the power law behavior in the two periods.

In the following section we describe the data, and present in short the Multifractal Detrended Fluctuation Analysis. The subsequent section deals with the results, and finally we draw the conclusions.

2. Data and methodology

2.1. Hot pixel data

The data analyzed in this work represent a part of a large database [44] provided by the Center for Time Prevision and Climatic Studies (Centro de Previso de Tempo e Estudos Climticos — CPTEC) of the Brazilian National Institute for Space Research (Instituto Nacional de Pesquisas Espaciais — INPE), as part of a large project for detection and monitoring of forest and wild fires in Brazil. The original data were used to find number n of hot pixels observed on every day of the monitored time interval. As shown in Fig. 1 strong seasonality with pronounced peaks in the month of September is observed, superimposed with pronounced fluctuations at finer scales.

In Table 1 and Fig. 2 we present the number of hot pixels detected per year by the NOAA-12 satellite in the considered time period, where a strong increase of the number of observed hot pixels in the second half of the period is observed.

2.2. Multifractal analysis

As opposed to simple fractals described by a single scaling exponent, multifractal time series are characterized by a hierarchy of scaling exponents that describe different scaling behavior of (many) interwoven subsets of the series [45]. In