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Computational comparison and pattern visualization of forest fires

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ABSTRACT

This paper analyses forest fire (FF) patterns based on information collected by the Canadian National Fire Database. The space-time dynamics of FF reveals characteristics that require advanced mathematical and computational methods. The study adopts the perspective of dynamical analysis to process the FF data considering amplitude, space and time. Several distinct techniques, such as dimensionality reduction, clustering and computer visualization unveil the relationships embedded in the data. The results reveal long term memory effects that demonstrate the usefulness of the proposed tools and motivate collecting further data related with this complex phenomenon.

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1. Introduction

Forest fires (FF) are phenomena that occur in many regions of Earth [1–4] destroying vast areas and compromising ecosystems [5–9]. The FF space-time series exhibit complex dynamical effects that pose considerable challenges to a robust modeling and motivate their study using present-day algorithmic methods [10,11]. FF are influenced by a plethora of natural and human issues, such as type of environment, weather, and efficiency of the warning, surveillance and suppression systems. Understanding the space-time evolution of FF will help in the implementation of advanced strategies for FF prevention and suppression [12,13]. The FF dynamics reveal long range memory and self-similarity that leads to the emergence of power-law (PL) characteristics [14–18]. Several authors [19,20] demonstrated that FF exhibit PL frequency-size distributions consistent with self-organized criticality. Nevertheless, some other suggest that a PL distribution of sizes may be too simple to describe completely FF [21]. Telesca et al. [22] investigated the time dynamics of FF and showed that the events exhibit time-clustering characteristics. They also addressed FF using fractal geometry [23]. Fletcher et al. [24] adopted the theory of scale invariance to model the burnt area in the forests of Amazon. Teplay and Veblen [25] proposed a method to understand long-term space-time FF dynamics in mixed-conifer and aspen forests, and studied the region of San Juan Mountains. Lopes and Machado [26–29] studied FF in Portugal and in the U.S. using hierarchical clustering and multidimensional scaling (MDS). The characteristics of FF recall also those exhibited by fractional-order systems [30–33]. Considerable progresses have been made in this area during the last years and relevant applications were reported [34,35], but to the author's bets knowledge no attempt has yet been made to tackle FF with the tools of fractional calculus.

This paper studies the FF space-time dynamics by analyzing a public domain database of events occurred in Canada during years 1980–2015. For that purposed several distinct computational and numerical tools are adopted, namely dimensionality reduction, clustering and computer visualization, that unveil some of the FF patterns. These algorithms are often used in the scope of complex systems that reveal analogies with the FF [14,16–18]. We consider the space-time series of burnt area as observations of the output of a multidimensional dynamical system that is influenced by many distinct factors. The study of these data will lead to conclusions about the system behavior [36].

In this line of thought, the paper is organized as follows. Section 2 introduces the dataset. Sections 4 and 3 process the FF data with respect to time and space, respectively, and discusses the results. Finally, Section 5 draws the main conclusions.

2. Dataset

The data used in this study are from the Canadian National Fire Database (CNFDB). The CNFDB is a collection of FF locations and perimeters as provided by Canadian fire management agencies, including provinces, territories, and Parks Canada [37]. The CNFDB

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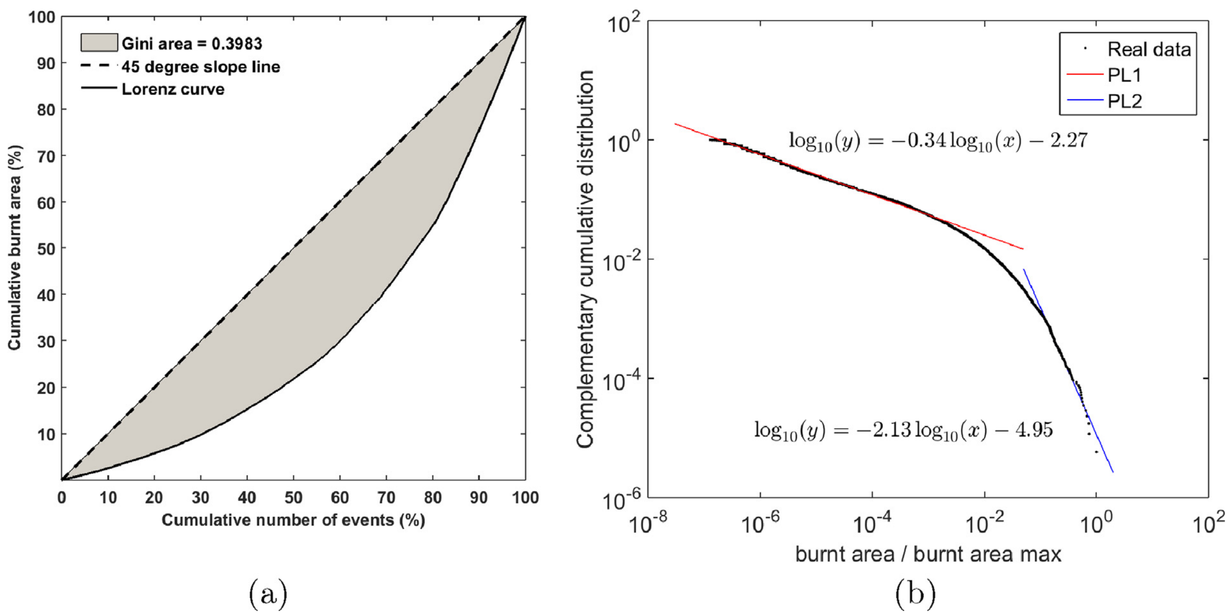

Fig. 1. Characterization of FF in Canada for the time period 1980–2015: (a) Lorenz curve relating the cumulative burnt area and the cumulative number of FF; (b) log-log plot of the complementary cumulative distribution of burnt area.

includes about 400,000 events for the period 1930 to 2016, where each record corresponds to one FF, with information about the date, time (with 1-day resolution), coordinates (latitude and longitude) and amplitude (burnt area in hectares).

The data analyzed herein were retrieved in December, 2016 but, by that date information for year 2016 was still incomplete. Moreover, to avoid errors due to incomplete data, namely those prior to 1980, we decided to consider only the period 1980–2015.

All FF sources are considered, namely natural causes, human negligence, or human intentionality, among others. Canada has about 9% of the world's forest. More than 7000 FF occur every year, consuming about 2.5 million hectares. Only 3% of the total FF destroy more than 200 hectares, but, on the other hand, they represent about 97% of the total burnt area.

In Fig. 1(a) we depict the Lorenz curve that relates the cumulative burnt area and the cumulative number of FF. The Gini coefficient (double of the Gini area) that measures the inequality among values of the frequency distribution of burnt area is 0.3983. This corresponds to moderate equality between the values of burnt area, since a coefficient close to zero means good equality, while a coefficient near 1 expresses large inequality among values. Fig. 1(b) represents the log-log plot of the complementary cumulative distribution function of burnt area. This distribution is approximated by a double PL with exponent values equal to 0.34 and 2.13, respectively, meaning that small/medium and large FF have quite different characteristics [14,38].

Fig. 2 depicts the burnt area and the number of FF per year during the period 1980–2015. It is visible an increase on both the number of FF and burnt area since year 2000. Nevertheless, the charts reveal a large volatility that pose difficulties to capture some trend, in case it exists.

These results illustrate through direct statistics the importance of using advanced tools for understanding the behavior of FF and characterizing the spatiotemporal patterns, if any, embedded in this complex phenomenon. For this purpose, in the sequel we adopt several mathematical and computational techniques common in the study of real-world complex systems.

3. Analysis of FF time patterns

The FF data may be interpreted as a sparse sequence of samples in space and time, measuring the daily burnt area. In fact, the FF data constitute a 4-dim problem, since we have 2 dimensions for space (latitude and longitude), 1 dimension for time, and 1 dimension for the amplitude. Comparing 4-dim data poses computational and algorithmic difficulties both due to the large number of records and to the sparsity of the information along the space and time dimensions of the 4-dim vector. Moreover, the FF evolve in space and time and, therefore, the recorded coordinates represent only the final part of the event. However, this effect is of minor importance, since we are not interested in the dynamics of each particular FF, and, on the contrary, we are considering the global FF dynamics along the decades.

We start by analyzing all FF occurred in the Canada territory in the period 1980–2015. This means that we consider only time and size, modeling the FF as Dirac impulses in time, with amplitude equal to the burnt area:

$$x_d(t) = \sum_{k=1}^{Q} A_k \delta(t - t_k), \tag{1}$$

where A_k represents the daily burnt area, t is time (with 1-day resolution) and Q is the total number of days in the period of analysis.

Processing the signal $x_d(t)$ by means of the Fourier transform (FT) we obtain:

$$\mathcal{F}\{x_d(t)\} = X_D(j\omega) = \int_{-\infty}^{+\infty} x_d(t) e^{-j\omega t} dt, \tag{2}$$

where $j = \sqrt{-1}$ and ω represents angular frequency. If we withdraw the first five harmonics, that is the frequency components related to the known FF seasonal periodicities, we obtain the frequency signal $\tilde{X}_D(j\omega)$. Approximating the magnitude of $\tilde{X}_D(j\omega)$ by a PL function results in:

$$|\tilde{X}_D(j\omega)| \simeq a\omega^{-b}, \quad a \in \mathbb{R}^+, \ b \in \mathbb{R}. \tag{3}$$

Fig. 3 depicts $|\tilde{X}_D(j\omega)|$ and the PL approximation, where $(a, b) = (14.8, 0.33)$. The high noise of the frequency plot is representative of the high stochastic nature of the time-space events.

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