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Investigating fire-induced behavioural trends in vegetation covers

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Abstract

The fire-induced variability in vegetation dynamics was analyzed by means of a fluctuation analysis applied to a time series of satellite SPOT-VEGETATION normalized difference of vegetation index (NDVI) data from 1998 to 2003. We used the detrended fluctuation analysis (DFA), which allows capturing persistent behavior in nonstationary signals. We analyzed four vegetation sites, two affected and the other two not affected by fires. Our results point out that the persistence of vegetation dynamics is significantly increased by the occurrence of fires.

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Keywords: Fires; Persistence; Detrended fluctuation analysis; Vegetation; NDVI

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1. Introduction

Fires can cause permanent changes in composition of vegetation community, decrease of vegetation covers, loss of biodiversity, soil degradation, alteration of landscape patterns and ecosystem functioning, thus resulting in speeding up desertification processes [1]. Furthermore, fires can contribute to alien plant invasion, patch homogenization, and create positive feedback in future fire susceptibility, fuel loading, fire spreading and its intensity [2]. The dynamics of vegetation in burned and unburned areas can be monitored by using satellite data, which provide a wide spatial coverage and internal consistency of data sets. Several indices can be used to perform such kind of remote sensing monitoring. In particular, normalized difference vegetation index (NDVI) obtained from the visible (Red) and near infrared (NIR) by using the following formula $\text{NDVI} = (\text{NIR} - \text{Red})/(\text{NIR} + \text{Red})$, is the most widely used index to follow the process of recovery after fire [3].

This paper aims to perform a dynamical characterization of burned and unburned vegetation covers, using time series of remotely sensed data of two fire-affected and two fire-unaffected sites. For this purpose, we used

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the detrended fluctuation analysis (DFA), which permits the detection of persistent properties in nonstationary signals.

2. Data set

We investigated four test sites: two fire-affected, Sortino (*Mediterranean shrubs, Quercus ilex*) and Sennariolo (*Mediterranean shrubs*) and two fire-unaffected, Magliano (*Quercus cerris, Quercus pubescens*) and Sfelicecirceo (*Mediterranean shrubs, Quercus ilex*), all located in Italy. For each site, we analyzed the 1998–2003 time series of 5 or 10 pixels (depending on the extension of the vegetation cover) of NDVI data derived from the sensor VEGETATION on board the SPOT satellite platforms. Each pixel has a spatial resolution of 1 km^2. Such data are available free of charge at the Vlaamse Instelling voor Technologisch Onderzock (VITO) Image Processing centre (Mol, Belgium) http://www.vgt.vito.be. In particular, we analyzed the ten-day (decade) maximum value of daily NDVI maps. The temporal evolution of decadal NDVI composition is regarded as an effective time window able to show the natural seasonal variations, the consequences of extreme climatic events and the man-induced damage suffered by ecosystems. The data were subjected to atmospheric corrections performed by CNES on the basis of the simplified method for atmospheric corrections (SMAC). Moreover, the considered NDVI composition also allows for reducing the contamination effects due to residual clouds, atmospheric perturbations, variable illumination and viewing geometry that are generally present in daily NDVI maps.

3. Detrended fluctuation analysis

Persistent signal fluctuations correspond to a $1/f^{\alpha}$-power spectrum, where f is the frequency and the scaling exponent $\alpha > 0$. By estimating 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 [4]. The DFA [5] avoids spurious detection of correlations that are artefacts 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. Very often we do not know the causes and the scales of these underlying trends [6]. The DFA method works as follows. In order to analyze the NDVI time series, we briefly present an introduction to the DFA, which is constituted by the following steps:

(1) Consider the decadal NDVI signal $x(i)$, where $i = 1,\dots,N$, and N is the total number of decades. 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 linear function, which represents the trend in that box. The y coordinate of the fitting line in each box is indicated by $y_n(k)$.

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

(5) For 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

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