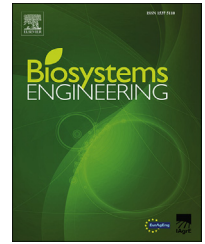




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Research Paper

Singularity maps applied to a vegetation index

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Agricultural drought quantification is one of the most important tasks in the characterisation process of this natural hazard. Recently, several vegetation indexes based on remote-sensing data have been applied to quantify it, being the Normalized Difference Vegetation Index (NDVI) the most widely used. Some index-based drought insurances define a drought event through the comparison of actual NDVI values in a given period with a NDVI threshold based on historical data of that period extrapolating this result spatially to the surrounded areas. Hence, the spatial statistical approach is very relevant and has not been deeply studied in this context.

Drought can be highly localised, and several authors have recognised the critical role of the spatial variability. Therefore, it is important to delimit areas that will share NDVI statistical distributions and in which the same criteria can be applied to define the drought event. In order to do so, we have applied for the first time in this context the method of singularity maps commonly used in localisation of mineral deposits. The NDVI singularity maps calculated for each season and different years are shown and discussed in this context. For this study we have selected a region that includes the whole Autonomous Community of Madrid (Spain). The resulting singularity maps show that areas where the NDVI follows theoretically a spatial normal/log-normal distribution ($\alpha \cong 2$) are widely scattered in the area of study and vary across seasons and years. Therefore, the extrapolation of normal/log-normal NDVI statistics should be applied only inside these areas.

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1. Introduction

1.1. Drought and vegetation indexes

Drought is one of the natural hazards with more impact on the planet and human life, becoming a natural disaster in extreme cases (Gouveia, Trigo, & DaCamara, 2009). Although there are

several definitions of drought, it can generally be defined as the temporary lack of water, relative to the normal supply, for a sustained period of time (Hayes, 2004; Keyantash & Dracup, 2002).

Drought quantification is one of the most important tasks in the characterisation of this natural hazard and can be approached in different ways (Sepulcre-Canto, Horion, Singleton, Carrao, & Vogt, 2012). One promising way is

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through indexes based on remote-sensing data (Dalezios, Blanta, Spyropoulos, & Tarquis, 2014) obtained by satellites or drones. These aircraft have spectro radiometric sensors installed on board (AVHRR, MODIS, among others) which are able to detect different frequency bands to obtain surface-Earth images at periodic time intervals. The combination of these frequency bands derives to Vegetation Indexes (VI). These indexes show the Photosynthetically Active Radiation (PAR) absorption of green leaves. The VI are associated with fundamental hydro-ecological processes such as precipitation, which in turn is also directly linked to photosynthesis and hence plant growth. The most widely used VI are: Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI) and Enhanced Vegetation Index (EVI).

1.2. Statistical approaches in VI spatial variability

It is important to note that more and more index-based agricultural insurances are defining a drought event through the comparison of the current VI value in a given period with a VI threshold based on historical data (Chantarat, Mude, Barrett, & Carter, 2013; Makaudze & Miranda, 2010). In this scenario, the statistical assumptions made to calculate this threshold will be crucial since different statistical approaches will lead to different conclusions.

The VI maps usually present a high variability in their values (Scheuring & Riedi, 1994). In the most common approach, the spatial variable under study is considered to be a random process and the main indicator measuring the spatial variability is the semivariogram, a second-order statistical moment of the spatial variable (Peebles, 1987). The most usual assumption is the “intrinsic hypothesis” where the semivariogram only depends on the lag distance (stationary process) and all the regionalised variables are considered Gaussian (Journal & Huijbregts, 1978).

There is an alternative approach to measure the spatial variability in singular physical processes by Multifractal Analysis (MFA). Singular processes are normally non-linear systems whose final results can be modelled by fractals or multifractals (Evertsz & Mandelbrot, 1992; Feder, 1989; Schertzer & Lovejoy, 1991). Fractality and multifractality (scaling laws) are emergent general features of ecological and geological systems (Saravia, Giorgi, & Momo, 2012; Turcotte, 1997), and they reflect constraints in their organisation that can provide tracks about the underlying mechanisms (Solé & Bascompte, 2006). Some examples of singular processes in the context of natural systems are: cloud formation (Schertzer & Lovejoy, 1987), rainfall (Veneziano, 2002), hurricanes (Sornette, 2004), etc. MFA should be used when a spatial distribution shows a singular character and extreme values (anomalies) are relevant (Cheng, 1999a). Outcomes of such singular processes are often described by positively-skewed distributions with Pareto upper-value tails (Agterberg, 1995; Cheng, Agterberg, & Ballantyne, 1994; Lavallee, Lovejoy, Schertzer, & Ladoy, 1993).

1.3. The singularity index

In the context of MFA, we can characterise the anomalous spatial behaviour of singular processes by the singularity

index or exponent. The mapping of singularity exponents in multifractal measures has proved to be a very effective tool in delineating areas with anomalies in measure distributions. Cheng (1999a, 2008) elaborated a local singularity analysis based on multifractal modelling that provides a powerful tool for characterising the local structural properties of spatial patterns. Taking the notation of MFA, the behaviour around a location x of a multifractal measure μ can be described as a power-law relationship:

$$\mu(B(x, r)) \sim r^{\alpha(x)}, \quad (1)$$

where $B(x, r)$ is a set centred at x with radius $r \rightarrow 0$. The exponent of this power-law model is the singularity exponent $\alpha(x)$ and characterises the degree of anomalous behaviour. The singularity exponent usually has finite values around the support topological dimension (E) and varies within a finite range from α_{min} to α_{max} . Singularity map is defined as the locus of the points x that have the same singularity exponent (Falconer, 2003), calculated by the expression:

$$\alpha(x) = \lim_{r \rightarrow 0} \frac{\ln \mu(B(x, r))}{\ln r}, \quad (2)$$

This tool has been successfully applied to detect anomalies in the concentration of an element (Cheng, 2001, 2006, 2007; Xie, Cheng, Chen, Chen, & Bao, 2007), which helps to delimit potential deposits (Cheng, 1999a). In the case of anomaly detection in element concentration maps, Cheng (2001) stated that the mean element concentration $Z(x)$, calculated for various cell sizes r centred at x , obeys a power-law with r :

$$Z(x) \sim r^{\alpha(x)-E}, \quad (3)$$

where $E = 2$ in this type of maps. This power-law is fulfilled in a certain range of r , $[r_{min}, r_{max}]$, obtaining a singularity map.

In the above work, points with $\alpha(x) \cong 2$ (where \cong means “approximately equal to”) are named as “non-singular locations” and represent areas with constant mean element concentrations. Points with $\alpha(x) \neq 2$ are named as “singular locations”, and we can differentiate areas with positive singularities ($\alpha(x) < 2$) corresponding to anomalously high values of mean concentration in a geochemical map, and negative singularities ($\alpha(x) > 2$) corresponding to low mean concentration values. Then, the Concentration–Area (CA) method was applied to calculate the threshold of positive and negative singularities (Liu, Xia, Cheng, & Wang, 2013). Therefore, calculating the singularity map for a geochemical concentration map may be used to characterise concentration patterns which provide useful information for interpreting anomalies related to local mineralisation processes.

Another useful interpretation of the singularity exponent is related to geostatistics (Cheng, 2008). This interpretation states that the majority of locations on the map where $\alpha(x) \cong 2$ (non-singular locations) follows either normal or lognormal distributions, whereas the singular locations (positive and negative singularities) on the map with $\alpha(x) \neq 2$ may follow extreme value Pareto distributions. The majority of common statistical techniques which require the assumption of normal distributions and the intrinsic hypothesis may not be effective for studying data with extreme value distributions, as happens in multifractal processes.

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