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STATISTICS

Lacunarity analysis of daily rainfall data in Pernambuco, Brazil

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ABSTRACT. Here we report a study of the temporal variation in daily rainfall recorded at meteorological stations in the state of Pernambuco, Brazil using the method of lacunarity to evaluate dry spell distribution. Results indicate coastal region rainfall has lower lacunarity and shows a more homogeneous behaviour with respect to dry spell duration. In the semiarid and dry regions rainfall series demonstrate higher lacunarity, indicating more complex behaviour and greater variation in dry spell duration. We show that clustering based on calculated lacunarity values can be used to identify geographical regions with characteristic temporal variability in rainfall pattern. For Pernambuco, three distinct spatial patterns were identified: one in the *Zona de Mata*, another in southern *Agreste* and *Sertão Pernambucano*, and third in *Sertão São Francisco* and the northern part of *Agreste*.

Keywords: fractal; meteorology; climatic phenomena.

Análise de lacunaridade de dados de precipitação diária em Pernambuco, Brasil

RESUMO. Neste trabalho, estudamos a variabilidade temporal da precipitação diária registrada em estações meteorológicas no estado de Pernambuco, utilizando o método de lacunaridade para avaliar a distribuição de períodos secos. Os resultados mostraram que, na região costeira, as séries de precipitação exibem menor lacunaridade, indicando comportamento mais homogêneo em relação à duração das secas. No semiárido e na região seca, as séries de precipitação demonstraram maior lacunaridade, indicando comportamento mais heterogêneo e larga distribuição da duração de períodos secos. Mostrou-se também que o agrupamento baseado em valores de lacunaridade pode ser utilizado para identificar regiões geográficas com comportamento temporal característico da precipitação. Para Pernambuco, foram obtidos três distintos padrões espaciais: um formado por estações localizadas na Zona de Mata, outro em Agreste e Sertão Pernambucano e o terceiro em Sertão São Francisco e parte norte de Agreste.

Palavras-chave: fractal; meteorologia; fenômenos climáticos.

Introduction

Hydrological processes (rainfall, streamflow, evaporation, infiltration, etc.) are characterised by nonlinearity and high levels of complexity (Sivakumar & Singh, 2012). The complexity of hydrological processes has been extensively studied over the last decades, using classical statistical methods (Espinoza-Villar et al., 2009; Santos, Pulido-Calvo, & Portela, 2010), chaos theory (Jayawardena & Lai, 1994; Sivakumar, 2001), fractals (Li & Zhang, 2007), multifractals (Tessier, Lovejoy, Hubert, Schertzer, & Pecknold, 1996; Kantelhardt et al., 2006) and information theory (Li & Zhang, 2008; Mishra, Özger, & Singh, 2009; Zhang & Singh, 2012). The Recent improvement in computational power, data acquisition technologies, geographic information systems (GIS) and networking facilities provide researchers with powerful tools to develop more efficient techniques to evaluate temporal and spatial variability and complexity of hydrological phenomena (Sivakumar & Singh, 2012). In view of these, the present study examines the utility of the lacunarity method for analysis of rainfall variability in the state of Pernambuco, Brazil. Rainfall is the most important hydrometeorological variable which is related to climate changes (Almazroui, Islam, Jones, Athar, & Rahman, 2012), crop yield (Lobell & Field, 2007; Verón, Abelleyra, & Lobell, 2015), primary production (Ye, Reynolds, Sun, & Li, 2013) and water supply (Zhou, Mahon, Walton, & Lewis, 2002). Understanding the spatiotemporal variation in rainfall is crucial for the development of planning and management strategies for rational and sustainable water resource use in river basins (Diaz, Weatherhead, Knox, & Camacho, 2007; Collischonn et al., 2007), and for evaluation and prediction of environmental alterations (Pearson & Dawson, 2003; Knapp et al., 2008).

The climate of the Brazilian Northeast (2-14°S, 35-46°W) is predominantly semiarid with high seasonal and inter-annual irregularity in rainfall. Extreme rainfall and droughts events are associated with such climatic phenomena as El Niño Southern Oscillation (Enso) and the meridional Sea Surface Temperature (SST) gradient. During the periods when Enso (SST) has negative (positive) value, the amount of rainfall is high. By contrast, positive (negative) values of Enso (SST) are characterized by low rainfall and prolonged droughts (Lucena, Servain, & Gomes-Filho, 2011). In the semiarid regions of the state of Pernambuco, there is an increase of short-lived torrential rains and high frequency of dry spells. Serious social, economic and environmental consequences, such as alterations in species distribution and water security of population, place this area in high climatic risks (Lacerda et al., 2015).

Besides diverse quantitative methods based on classical statistics that have been applied used to analyse spatiotemporal variation of dry and wet periods (Vicente-Serrano & Beguería-Portugués, 2003; Nastos & Zerefos, 2009; She & Xia, 2013), methods recently developed in complex system science have also been utilized in hydrological studies, and have shown promise in providing better understanding of temporal variability and intermittency of rainfall (Royer, Biaou, Chauvin, Schertzer, & Lovejoy, 2008; Mascaro, Deidda, & Hellies, 2013; Lana, Burgueño, Serra, & Martínez, 2017).

Rainfall in Pernambuco State is characterised with high irregularity in both temporal and spatial distribution, due to the economic, political, sociological and ecological importance of studying such variability, we analysed daily data from a series of pluviometric stations widely distributed across the state. We use a lacunarity method that was recently applied to rainfall data and which showed promise as a method to further understanding of temporal variability and fragmentation of rainy and dry periods (Martínez, Lana, Burgueño, & Serra, 2007; Pons, Javier, Martínez-Santafé, Larrocha, & Burgueño, 2010; Lucena, Stosic, & Cunha-Filho, 2015).

Material and methods

Study area

The study was carried out in Pernambuco State, central-eastern northeastern Brazil (Figure 1). The State has an area of 98,311 km² and, a population of 9,277,727 habitants, and is bounded to the east by the Atlantic Ocean and by its borders with the states of Paraiba (N), Alagoas (SE), Piauí (W), Ceará (NW) and Bahia (S). It is located between parallels 7° 18' 17" and 9° 28' 43" S and the meridian 34° 48' 15" and 41° 21' 22" W (Silva, Moura, França, Lopes, & Silva, 2011).

Figure 1. Pernambuco State and its administrative sub-regions.

Pernambuco has diversified climatic conditions due to its geographical position, vegetation and topography. According to Koppen-Geiger climate classification, two different climate systems characterise the area: the humid tropical climate As' (predominant on the coast) and semiarid BSh (predominant in the interior). Rainfall occurs in autumn and winter in the coastal region, and in *Sertão*, respectively (Silva, Moura, & Klar, 2014). The humid tropical climate occurs in the Metropolitan Recife Area (*Região Metropolitana do Recife* - RMR), and part of *Zona de Mata*, and has an annual average temperature of 25°C and average rainfall of 1500 to 2000 mm. The semiarid climate is found in *Sertão* and part of *Agreste* region and has an annual average temperature of 25°C and an average rainfall lower than 600 mm (Silva et al., 2014).

Data

We used daily precipitation data from 94 meteorological stations in Pernambuco (from January 1, 2005 to May 31, 2015) collected by the Pernambuco State Agency for Water and Climate (Apac, *Agência Pernambucana de Águas e Clima*). Figure 2 shows the spatial distribution of 94 municipalities (colored red) containing the meteorological stations used in this study.

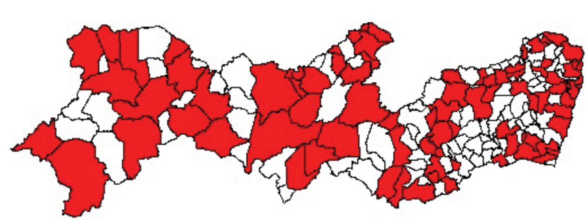

Figure 2. Spatial distribution of 94 Pernambuco municipalities with meteorological stations used in this study.

Lacunarity analysis was used to characterize time series of precipitation regime for all meteorological stations in study.

Lacunarity

The concept of lacunarity was introduced by Mandelbrot (1982) as a measure of the distribution of gap sizes in a fractal object. Geometric objects with gap sizes distributed over a wide range have greater lacunarity than those with smaller and more uniform gaps. Lacunarity is related to the deviation of a geometric object from translational invariance (Gefen, Meir, Mandelbrot, & Aharony, 1983). Homogeneous and translationally invariant geometric objects have low lacunarity, while heterogeneous and non-translationally invariant geometric objects have high lacunarity. Translational invariance (and lacunarity) is also scale dependent: objects that are heterogeneous at small scale can appear homogeneous at higher scale and vice versa. Lacunarity can be used with both binary and quantitative data in one, two and three dimensions (Plotnick, Gardner, Hargrove, Prestegaard, & Perlmutter, 1996; Dong, 2009).

Various methods for calculating lacunarity (Mandelbrot, 1982; Gefen et al., 1983; Dong, 2000) have been developed, among these the gliding box algorithm (Allain & Cloitre, 1991) has been extensively used in medicine (Zaia, Eleonori, Maponi, Rossi, & Murri, 2006), ecology (Malhi & Román-Cuesta, 2008), geology (Roy, Perfect, Dunne, Odling, & Kim, 2010), food technology (Velazquez-Camilo, Bolaños-Reynoso, Rodriguez, & Alvarez-Ramirez, 2010), urban planning (Myint & Lam, 2005) and climatology (Martínez et al., 2007; Lana, Burgueño, Serra, & Martínez, 2015).

In the current study, we apply the gliding-box algorithm (Allain & Cloitre, 1991) on one-dimensional set constructed from temporal series of daily rainfall. In this analysis, lacunarity is a measure of the distribution of gaps defined as sequences of consecutive days with rainfall values below a chosen threshold (Martínez et al., 2007). In this study, the thresholds of 0 and 10 mm day^{-1} of rainfall were used. Large lacunarity values imply large gaps and greater heterogeneity of dry spells, whereas small values imply smaller sizes of gaps, indicating a more uniform rainfall distribution (Mandelbrot, 1982).

To calculate lacunarity, we first determined $\mathrm{n(s,r)}$, the number of sliding windows of size r (time steps) containing s occupied sites (time steps in which the precipitation exceeds the chosen threshold). The probability $\mathrm{p(s,r)}$ is estimated by Equation 1:

$$\mathrm{p(s,r)} = \frac{\mathrm{n(s,r)}}{\mathrm{N(r)}} \tag{1}$$

where:
$\mathrm{N(r)} = \mathrm{L} - \mathrm{r} + 1$ is the total number of windows of size r, and L is the total length of record, including segments of occupied sites and gaps. Lacunarity is now defined by Equation 2:

$$\mathrm{L(r)} = \frac{\mathrm{M2(r)}}{[\mathrm{M1\ (r)}]^2} \tag{2}$$

where:
$\mathrm{M1(r)}$ and $\mathrm{M2(r)}$ are the first and second moment of $\mathrm{p(s,r)}$, given by Equation 3:

$$\mathrm{M1(r)} = \sum_{\mathrm{s}=1}^{\mathrm{r}} \mathrm{s} \cdot \mathrm{p(\,s\,,r)} \tag{3}$$

and Equation 4:

$$\mathrm{M2(r)} = \sum_{\mathrm{s}=1}^{\mathrm{r}} \mathrm{s}^2 \cdot \mathrm{p(\,s\,,r)} \tag{4}$$

respectively. For any scale free process lacunarity decreases with window size as power law Equation 5:

$$L(r) = \alpha\, r^{\beta} \tag{5}$$

where:
scaling exponent β can be determined as the slope of linear regression of $\log[L(r)]$ versus $\log(r)$ (Martínez et al., 2007).

To obtain the most similar lacunarity groups we used k-means grouping analysis, for which we used lacunarity window values of 2 and 8 days of evaluation, as well as the beta exponent of lacunarity.

K-means

Clustering analysis is a multivariable statistical methodology used to group observation data (points in multidimensional parameter space) into homogeneous subsets. The k-Means method is probably the most widespread clustering technique. This procedure agglomerates points in a manner that minimises within-group variability, and maximises between-group variability (Everitt, Landau, Leese, & Stahl, 2001; Everitt, 2005; Bravo-Cabrera, Azpra-Romero, Zarraluqui-Such, Gay-García, & Estrada-Porrúa, 2012).

The k-means algorithm, developed by Hartigan and Wong (1979), requires as input a matrix of M points in N dimensions and a specification of the number of K clusters and proceeds as follows.

1) First, the observed M points are randomly attributed one of the K cluster labels, and the K cluster centroids are calculated.

2) In the next step, the distance of each of the M points to each of the centroids is calculated, and if necessary, each point is relabelled so as to correspond to the nearest centroid.

3) After relabeling all of the points, new cluster centroids are calculated.

4) Steps 2-3 are repeated until no further point relabeling occurs.

The above k-means algorithm therefore represents a general deterministic procedure with which to search for a k-partition with minimum inter-cluster distances. This is done by iteratively moving points from one cluster to another, until no further movements will diminish the objective function (integral inter-cluster separation). While the k-means algorithm depends on the (random) initial choice of cluster labels that may lead to ambiguities when cluster labels are not well separated (Stošić, 2009), several runs with independent random labels usually lead to optimal solutions, and the k-means algorithm remains one of the simplest, fastest and most reliable (and therefore most widely used) clustering algorithms. Clustering was evaluated by criterion of sum squares of residues.

Results and discussion

Initially, and for all 94 meteorological stations, the maximum and average rainfall values were used to characterize precipitation of the studied region. Following lacunarity characterization, calculations were performed using 2 and 8 day evaluation windows and thresholds of 0 and 10 mm of precipitation and the beta exponent of lacunarity was also evaluated for the 0 and 10 mm thresholds. Finally, k-means grouping analysis was performed to obtain groups of meteorological stations with similar lacunarity values for the 0 and 10 mm precipitation thresholds.

Figure 3 shows maximum and average daily rainfall during the study period for all 94 meteorological stations. The highest maximum daily rainfall value was found in the metropolitan Recife area (RM and the southern part of *Zona de Mata*), while the lowest maximum values were found in *Moxotó*, *Pajeú* and in some parts of *Agreste Meridional* (Figure 3a). For average daily rainfall, highest averages occurred in the coastal region (capital, south and north parts of *Zona da Mata*), while lowest averages occured for meteorological stations located in *Sertão* and *Agreste Setentrional* regions (Figure 3b).

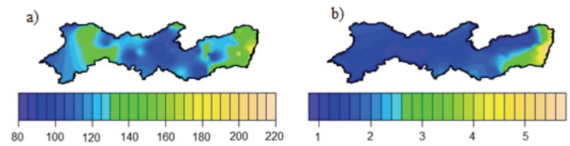

Figure 3. Maximum (a) and average (b) values (mm) of daily rainfall for 94 meteorological stations in Pernambuco State, northeastern Brazil.

Figure 4 shows the spatial distribution of lacunarity for the 0 mm threshold (only rainy and non-rainy days are considered) for two window sizes: 2 days and 8 days. For all meteorological stations, the lacunarity values decrease with window size, indicating a more uniform gap distribution (periods of consecutive days without rain) on a scale of 8 days. It is also seen in Figure 4 that for both window sizes lacunarity values are lower in the coastal region (RMR, south and north parts of *Zona de Mata*), indicating a more homogeneous temporal rainfall distribution. Lacunarity values increase in the *Sertão* and *Agreste* regions indicating a greater heterogeneity in dry period duration.

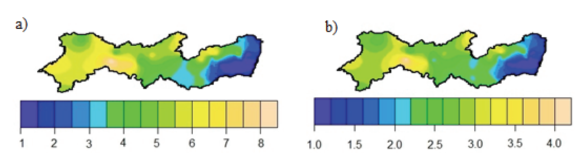

Figure 4. Empirical lacunarity of 94 meteorological stations utilising a 0 mm precipitation threshold and windows of 2 (a) and 8 (b) days.

Figure 5 shows three different patterns of lacunarity when a threshold of 10 mm of rainfall was deployed. The first pattern comes from stations located in RMR, north and south regions of *Zona de Mata*, which showed the lowest lacunarity values (along with the highest daily average rainfall and the highest daily maximum) indicating uniformly distributed rainfall. The second pattern is from the *São Francisco Sertão*, *Araripe*, and also part of *Pajeú Sertão*, *Moxotó* and *Itaparica*, which presented the highest lacunarity values (and the lowest average and daily maximum rainfall) indicating less rain and a larger distribution of dry spells. The third pattern includes stations in *Agreste* and also some stations in *Pajeú*, *Moxotó* and *Itaparica* which had intermediate lacunarity values and both higher and lower daily average and daily maximum values, indicating that in this region rainfall is moderately fragmented but shows variation in rainfall amounts.

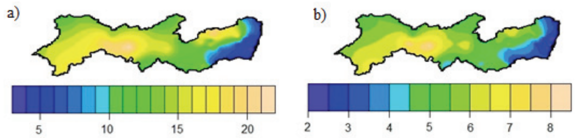

Figure 5. Empirical lacunarity from 94 meteorological stations using precipitation thresholds of 10 mm and windows of 2 (a) and 8 (b) days.

Figure 6 shows the spatial distribution of lacunarity exponent β (calculated using the window size 2-256 days) for the 0 and 10 mm rainfall threshold. Figure 6a shows three β exponents patterns for the 0 mm threshold: one formed by the *Sertão* stations (the highest β, and lowest average and daily maximum rainfall values), indicating a greater rainfall variability on different temporal scales. The second pattern is formed by the *Agreste* stations, and the third pattern comprises of the RMR stations, south and north regions of *Zona da Mata* (the lowest β, and the highest average and daily maximum rainfall values) indicating a more uniform rainfall pattern when analysed at different temporal scales. When the 10 mm threshold was used (Figure 6b), the highest β exponent values are from stations in the *Sertão* and parts of the *Agreste Setentrional*, while lowest β values with from stations located in RMR, southern and northern parts of *Zona de Mata* and part of the *Agreste Meridional.*

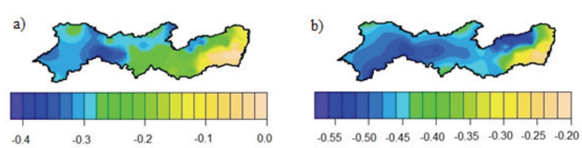

Figure 6. Lacunarity exponent β for 94 meteorological stations and precipitation thresholds of 0 (a) and 10 mm (b).

Figure 7 shows the clustering of 94 meteorological stations obtained by the k-means method using the lacunarity exponent β and lacunarity values for 0 and 10 mm thresholds with window sizes of 2 and 8 days. Three groups of stations can be seen: the first group is formed by stations located in RMR, and southern and northern parts of *Zona de Mata*; the second by those in the *São Francisco Sertão*, *Central Sertão* and parts of *Araripe, Pajeú, Moxotó* and *Itaparica*, and the *Agreste Meridional*. The third pattern is formed by stations located in *Agreste Central*, *Agreste Meridional,* part of *Agreste Setentrional* and parts of *Araripe, Pajeú* and *Moxotó*. Spatial variability of rainfall in northeastern Brazil (including Pernambuco State) has been studied extensively (Lima-Moscati & Gan, 2007; Hastenrath, 2012; Rao, Franchito, Santo, & Gan, 2016). However, much less is known about the local spatial characterization of precipitation regimes within the state which is crucial for agricultural planning and water resources management.

Nóbrega, Farias, and Santos (2015), used extreme climatic indices to evaluate spatial and temporal variability of rainfall in Pernambuco and found similar results: with regard to the occurrence of extremely dry and rainy events the middle section of the RMR showed the greatest regularity of occurrence of rainy and dry episodes, while in *Agreste* extremely dry episodes predominated. The third region, *Sertão,* had the highest number of extremely dry episodes. Silva et al. (2014) estimated monthly climatic water balance across the state of Pernambuco using data from 20 years of observations from 45 climatological stations, and constructed a climatic classification to determine agro-climatic zones. These are resemble the spatial regions obtained here with lacunarity analysis. Similar results were achieved by Nery et al. (1998), using multivariate analysis methods. They found several spatial groups formed by rainfall stations: *Zona de Mata, Agreste*, two groups in *Sertão* zone (*Sertão Pernambucano* and *Sertão São Francisco*) and one group in the border region with *Paraíba* State. Lacunarity analysis also found differences between *Sertão Pernambuco, Sertão São Francisco, Zona de Mata* and *Agreste*.

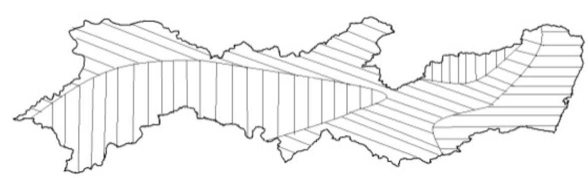

Figure 7. Clustering of 94 meteorological stations using k-means methodology.

Conclusion

In the current study we investigated the temporal dynamics of rainfall in the state of Pernambuco, Brazil, using the lacunarity method. The large lacunarity values observed in the *Sertão* and *Agreste* regions indicate greater heterogeneity in the distribution of dry spell duration with consequently less intensive and more fragmented rainfall, while lacunarity small values observed in the coastal region indicated greater rainfall, with a more homogeneous temporal distribution of consecutive rainy days. Using the lacunarity values and the lacunarity exponent β it was possible to classify three rainfall patterns (with respect to distribution of duration of dry periods) in Pernambuco State: i) a pattern formed by stations located in the coastal area, ii) another in *Agreste* and *Sertão Pernambucano,* and iii) a third in *Sertão São Francisco* and the northern part of *Agreste* on the border with *Paraíba* State. These results agree with current understanding of rainfall patterns in this region, showing the potential of lacunarity analysis as a means of quantitatively distinguishing between different rainfall regimes. We expect that the current findings can contribute to providing a basis for agriculturalists and water resources planners for reducing the consequences of extreme weather phenomena (droughts, floods, etc.), and that they may also aid the development of the current understanding of spatiotemporal patterning of rainfall variability in the of Pernambuco State, in particular, and that of the northeast of Brazil in general.

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