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Are droughts occurrence and severity aggravating? A study on SPI drought class transitions using loglinear models and ANOVA-like inference

E. E. Moreira[1], J. T. Mexia[1], and L. S. Pereira[2]

[1]CMA – Center of Mathematics and Applications, Faculty of Sciences and Technology, Nova University of Lisbon, 2829-516 Caparica, Portugal
[2]CEER – Biosystems Engineering, Institute of Agronomy, Technical University of Lisbon, Tapada da Ajuda, 1349-017 Lisboa, Portugal

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Correspondence to: E. E. Moreira (efnm@fct.unl.pt)

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Abstract

Long time series (95 to 135 yr) of the Standardized Precipitation Index (SPI) computed with the 12-month time scale relative to 10 locations across Portugal were studied with the aim of investigating if drought frequency and severity are changing through time. Considering four drought severity classes, time series of drought class transitions were computed and later divided into 4 or 5 sub-periods according to length of time series. Drought class transitions were calculated to form a 2-dimensional contingency table for each period. Two-dimensional loglinear models were fitted to these contingency tables and an ANOVA-like inference was then performed in order to investigate differences relative to drought class transitions among those sub-periods, which were considered as treatments of only one factor. The application of ANOVA-like inference to these data allowed to compare the four or five sub-periods in terms of probabilities of transition between drought classes, which were used to detect a possible trend in time evolution of droughts frequency and severity that could be related to climate change. Results for a number of locations show some similarity between the first, third and fifth period (or the second and the fourth if there were only 4 sub-periods) regarding the persistency of severe/extreme and sometimes moderate droughts. In global terms, results do not support the assumption of a trend for progressive aggravation of droughts occurrence during the last century, but rather suggest the existence of long duration cycles.

1 Introduction

Drought is a normal recurrent feature of climate, which occurs in all climatic zones. There are many definitions for drought; in this study the one proposed by Pereira et al. (2009) is assumed: Drought is a natural but temporary imbalance of water availability, consisting of a persistent lower-than-average precipitation, of uncertain frequency, duration and severity, of unpredictable or difficult to predict occurrence, resulting in diminished water resources availability, and reduced carrying capacity of the ecosystems (Pereira et al., 2009). Thus, short dry periods or dry spells, also often called droughts, are excluded from our analysis. There are various approaches for assessing drought severity, e.g. meteorological, agricultural, hydrological and socioeconomic. The first three approaches deal with ways to measure drought as a physical phenomenon, particularly using drought indices, and the last one deals with drought in terms of supply and demand (US National Drought Mitigation Cente, 2006). Drought indices are numerical figures incorporating mainly values of hydro-meteorological indicators. Meteorological drought indices respond to weather conditions that have been abnormally dry or abnormally wet. Precipitation based drought indices are the first indicators of droughts, since hydrological droughts may emerge considerable time after a meteorological drought has been established (Wilhite and Buchanan-Smith, 2005), due to the effect of storage. Consequently, precipitation-based drought indicators are the basic tools for a drought early warning system.

The Standardized Precipitation Index (SPI), (McKee et al., 1993, 1995), is often used for the identification of drought events and to evaluate their severity thus defining drought classes. The SPI is widely used because it allows a reliable and relatively easy comparison between different locations and climates (Bordi et al., 2009; Raziei et al., 2008). It has the advantage of statistical consistency and the ability to reflect both short-term and long-term drought impacts (Steinemann et al., 2005) since it may be computed on shorter or longer time scales, which reflect different lags in the response of water cycle to precipitation anomalies. Another advantage of SPI is that, due to its standardization, its range of variation is independent on the aggregation time scale of reference, as well as on the particular location and climate. Therefore, SPI values are more suited to be used as drought triggers, i.e. thresholds that determine when drought management actions should begin and end (Steinemann et al., 2005). The stochastic properties of the SPI time series can be used for predicting the likelihood and potential severity of future droughts, thus assisting in drought management (Moreira et al., 2008; Paulo et al., 2005; Paulo and Pereira, 2007). The 12-month time scale, as well as larger time scales, identifies dry periods of long duration which relate with the global impact of drought on hydrologic regimes and water resources of a region (Paulo et al.,

2003; Paulo and Pereira, 2006); differently, shorter time scales of 3 to 6 months are more useful to detect agricultural droughts. For the Portuguese conditions, where a dry period of near 6 months occurs, droughts impacting the hydrologic regime are better assessed when using the 12-month time scale (Paulo and Pereira, 2006). Hence, former studies on drought variability or on prediction of drought class transitions were performed with the SPI 12-month.

It is common in our time the idea that water resources have been decreasing in consequence of several causes, mainly due to less precipitation in certain regions of the planet, like the Mediterranean basin, as a result of climatic changes. In particular, it is often said that drought events are becoming more frequent and/or more severe due to climate change (Brunetti et al., 2004; Huntington, 2006; Szép et al., 2005; Richter and Semenov, 2005). In fact, dry spells are foreseen to be in augmentation in Europe due to climate change (Beniston et al., 2007), as well as hydrological droughts (Lehner et al., 2006). Differently, results of our former studies led to conclude that droughts are not more frequent or having an increased severity (Moreira et al., 2006), rather a possible occurrence of cycles in precipitation has been detected (Moreira et al., 2008). Also, results by Bordi et al. (2009) and Raziei et al. (2011) are in agreement with the hypothesis that droughts are not in augmentation. Mishra et al. (2010), regarding the Midwestern United States in the period 1916–2007, indicate that the study region is experiencing reduced extreme and exceptional droughts with lesser areal extent in recent decades (Mishra et al., 2010). An analysis of risk of dryness in Italy did not evidence climate change effects on this domain (Moonen et al., 2002). Also, the analysis of extreme rainfall events in Ireland show that a much greater proportion of extremes have occurred in the period since 1975 and also it was detected an increase in annual precipitation after this date (Kiely, 1999). A study on changes in streamflow in Duero River, it has shown that decreased discharges essentially related to land use changes (Morán-Tejeda et al., 2002).

The statistics of extremes has been widely used to study hydrologic extremes. Katz et al. (2002) approached this topic and discussed the anticipated intensification of the hydrologic cycle as part of global climate change (Katz et al., 2002). Raje and Mujumdar (2010) using two approaches for hydrologic drought prediction obtained an increasing probability of extreme, severe and moderate droughts and decreasing probability of normal and wet conditions in Orissa, India as a result of climate change (Raje and Mujumda, 2010). In a study on streamflow droughts in Europe, it is said that "scientists generally agree that the global hydrological cycle will intensify and suggest that extremes will become or have already become more common" (Hisdal et al., 2001). However, authors also wrote "Despite several reports on recent droughts in Europe, the non-parametric Mann-Kendall test and a re-sampling test for trend detection showed that it is not possible to conclude that drought conditions in general have become more severe or frequent. The period analyzed and the selection of stations strongly influenced the regional pattern. Within the period 1962–1990 examples of increasing drought deficit volumes were found in Spain, the eastern part of Eastern Europe and in large parts of the UK, whereas decreasing drought deficit volumes occurred in large parts of Central Europe and in the western part of Eastern Europe. Trends in drought deficit volumes or durations could, to a large extent, be explained through changes in precipitation or artificial influences in the catchment. Changes in the number of drought events per year were determined by the combined effect of climate and catchment characteristics such as storage capacity" (Hisdal et al., 2001). Also for Europe, Bordi et al. (2009), using data sets from 1949 to February 2009, have noted in the time series of drought and wetness area coverage (number of grid points above/below the severity threshold) a remarkable linear trend until about the end of the last century, which is reversed in the last decade. This recent trend reversal is an indication of a nonlinear trend, which is more pronounced on the hydrological time scale. The nonlinear trend analysis was performed based on the time series of the principal component (PC) associated to the first spatial SPI-eigenvector after embedding it in a time delay coordinate system using a sliding window of 70 months (singular spectrum analysis). Nonlinearity appears as a clear feature on the hydrological time scale (Bordi et al., 2009).

Regarding Iran, Raziei et al. (2008) found a long-term decreasing trend towards dry periods in the northern region, while an increasing but weak long-term trend has been observed in the southern sub-regions, though they are not statistically significant (Raziei et al., 2008). Seager (2007) regarding the turn of the century North American drought, wrote "Except in southern South America the global pattern of precipitation anomalies of the turn of the century drought is similar to that during the five prior droughts. These comparisons suggest that the earlier period of this most recent drought is the latest in a series of multiyear droughts forced by persistent changes in tropical Pacific Ocean temperatures. Warm tropical North Atlantic Ocean temperatures may play a secondary role" (Seager, 2007). More recently, Seager et al. (2009), in a study using observations of precipitation and model simulations forced by historical sea surface temperatures from 1856–2007, wrote "The recent drought in Southeastern United States, forced by reduced precipitation and with reduced evapotranspiration, has no signature of model-projected anthropogenic climate changes" (Seager et al., 2009b). In another paper they wrote "While the last decade or so in north and central México has been drier than preceding decades, the associated continental pattern of hydroclimate change does not fit that which models project to occur as a consequence of rising greenhouse gases and global warming. However, models robustly predict that México will dry as a consequence of global warming and that this drying should already be underway. At least for now, in nature, this is likely obscured by strong natural atmosphere-ocean variability" (Seager et al., 2009a).

Hence, despite the uses of different statistical tools in the analysis, still it is far from existing a global consensus regarding drought increasing of intensity and frequency in various regions of the planet. To be noted that uncertainty is present in climate change impact studies as analyzed by Droogers et al. (2007) and Olesen et al. (2007). However, since the concept of drought is different among authors of related studies, it is more difficult to find if drought or dry spells are influenced by climate change. The present study is therefore one more contribution to the discussion.

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In general, the purpose of this study is to analyze the historical frequency and duration of meteorological drought in Portugal. In particular, the objective of this study is to detect a possible trend in time evolution of droughts frequency and severity through the analysis of drought class transitions, which could be related to climate change, or instead, the occurrence of large cycles originated by a natural variability. The method used in this study is not commonly used for detection of trends in hydrology and climatology as are for example linear regression methods (Moonen et al., 2002; Mazvimavi, 2010; Shang et al., 2011; Shao et al., 2011). Other authors used principal component analysis to observe the spatial and temporal variability of drought and assess linear and no-linear trends (Bordi et al., 2004, 2006; Raziei et al., 2009).

This analysis is based on the SPI due to its above mentioned advantages, and in loglinear modeling, which has shown to be an adequate tool for drought class transitions analysis and for short-term forecast of SPI class transition probabilities (Moreira et al., 2006, 2008). The loglinear modeling, done upon the contingency tables for SPI drought class transitions, was used to obtain probability ratios, named Odds, and their confidence intervals, that allowed the comparison of different sub-periods of the same time series (Moreira et al., 2006, 2008). However, the Odds confidence intervals some times were too large, therefore not enough reliable, thus calling for adopting a more robust probability analysis. Since loglinear models proved well for analyzing and predicting transitions between successive SPI drought classes (Moreira et al., 2006, 2008), the adjusted models were used as a base for the current ANOVA-like inference approach. Suhailaa et al. (2011) used functional data analysis and one way functional analysis of variance to compare rainfall patterns between regions and find significant differences between regions, in Peninsular Malaysia. The ANOVA-like inference is a very robust and sensitive method to find variability and allows to locate significant differences between treatments. In this study, it was used to find significant differences on the number of drought class transitions between equivalent sub-periods of the same time series. So, the sub-periods of each time series are considered as treatments in the current ANOVA.

2 Data, SPI time series and division in sub-periods

The data used in this study is constituted by long time series of monthly Standardized Precipitation Index in a 12-month time scale (SPI-12) for 10 meteorological stations located in Portugal (Fig. 1).

The time series duration is not the same for all stations. Their size varies between 95 and 135 yr. In Table 2 are presented the identification and time series duration for each station.

The methods used to assess the quality of precipitation data series and to compute the SPI at the 12-month time scale are described in Paulo et al. (2003, 2005). The annual precipitation data sets used in SPI computation were investigated for randomness, homogeneity and absence of trends using the autocorrelation test (Kendall τ), the Mann-Kendall trend test and the homogeneity tests of Mann-Whitney for the mean and the variance (Helsel and Hirsch, 1992). As a result, only the time series not rejected by these tests at 5 % significance level were included in the study. In addition, the appropriateness for using the gamma distribution to compute the 12-month time scale SPI for the south and north of Portugal, was verified using non-parametric tests, namely the Chi-square test. SPI computation is described in former studies (Paulo et al., 2003, 2005; Paulo and Pereira, 2006, 2007).

The SPI time series were converted into drought classes according to Table 1. The severity drought classes adopted, also defined in Table 1, are modified from those proposed by McKee et al. (1993, 1995) by grouping the severe and extremely severe drought classes. This modification was done for modeling purposes since transitions referring to the extremely severe drought classes are much less frequent than for other classes; thus, a possible bias is avoided since too many zeros in the contingency tables cause problems in the fitting.

In order to achieve the final goal of this study – perceive if there is a trend for drought aggravation – the large duration time series (from 1872 to 2007) were divided into 5 or 4 shorter sub-periods of different size with the intent of statistical comparison. The

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time series division into 5 or 4 different sub-periods (depending of the time series total duration) is presented in Table 2. All sub-periods but the first have the same length for all locations.

In a previous study (Moreira et al., 2006), a first attempt was done just by dividing smaller time series into 3 sub-periods of similar duration (22/23 yr), because 3 was the minimal number in order to find either a cycle or a trend. However, if there is a cycle, it is not expectable that periods of drought recurrence should have exactly the same duration in every location. It is more likely that they refer to a larger range as for previous results (Moreira et al., 2008). Differently, if for some sites there is a significant trend of progressive increasing in droughts occurrence and severity, the successive sub-periods should present significant differences between them. It can be observed that, excepting for the sites in northern Portugal, there are sub-periods with much less events of moderate and severe/extreme droughts when compared with the previous and the subsequent sub-period (Figs. 2 and 3). Thus, the sub-periods were defined according to this perceived dynamics in order to gain accuracy when comparing them.

After dividing the time series, the number of one step transitions between any drought class was counted for each sub-period in order to form a 2-dimensional 4×4 contingency table with $N = 16$ cells each one. An example of these contingency tables is presented in Table 3, where the 5 contingency tables resulting from the division of the Porto time series into 5 sub-periods can be observed.

The observed frequencies, denoted by $n_{h,j}, h, j = 1, \ldots, 4$ on that table, are the number of times that it occurs the drought class h in a given month, followed by the drought class j in the next month (number of transitions between drought classes in successive months). In each pair of consecutive months, the first one is the entry month, while the other is the exit month.

In these contingency tables, since the sub-periods have different sizes, the observed frequencies were weighted in order to make it possible the comparison between the 5 (or 4) sub-periods in terms of the number of drought class transitions.

3 Modeling and methods of analysis

Loglinear models were fitted to contingency tables for the different stations. The adjusted models were used to carry out an ANOVA like-inference to compare the 4 or 5 sub-periods. These sub-periods correspond to the treatments of a one-way ANOVA.

Previous studies (Moreira et al., 2006, 2008) led to adjust to these contingency tables the quasi-association (QA) loglinear models (Agresti, 1990). Denoting by $m_{h,j}$ the mean value $E(n_{h,j})$ of $n_{h,j}$, $h, j = 1, \ldots, 4$, also called expected frequency, the QA loglinear models for two-dimension contingency tables have the following formulation

$$w_{h,j} = \log m_{h,j} = \lambda + \lambda_h^r + \lambda_j^c + \beta \times h \times j + \delta_h I(h = j) \tag{1}$$

where λ is the constant parameter also designated by the grand mean; λ_h^r is the parameter representing the row effect, i.e. the effect of drought class h of the entry month, $h = 1, \ldots, 4$; λ_j^c is the parameter representing the column effect, i.e. the effect of drought class j of the exit month, $j = 1, \ldots, 4$; β is the linear association parameter between rows and columns; δ_h is a parameter related to the h-th diagonal element of the contingency table, $h = 1, \ldots, 4$ and $I(h = j)$ takes the value 1 when the condition $h = j$ holds and the value 0 otherwise. The expected frequencies m_{hj} represent the expected number of transitions between drought classes h and j in two consecutive months during each sub-period. The word "effect" refers to any deviation above the mean. The QA loglinear models allow linear-by-linear association of the main diagonal of the contingency tables and are adequate to fit to squared tables (when the number of columns and lines are equal) with ordered categories, resulting from a pairwise comparison of dependent samples, which is the case.

In adjusting these models it is assumed that the $n_{h,j}, h, j = 1, \ldots, 4$, were values taken by independent Poisson distributed variables (Agresti, 1990). The assumption of independency of the $n_{h,j}$, $h, j = 1, \ldots, 4$ could be considered because transitions between drought classes in successive months mainly depend on the amount of precipitation occurring in those months, not on previous months (Paulo and Pereira, 2007). Then, the maximum likelihood estimators (MLE) $\hat{\lambda}$, $\hat{\lambda}_h^r$, $\hat{\lambda}_j^c$, $\hat{\beta}$, $\hat{\delta}_h$ and $\hat{m}_{h,j}$, $h,j = 1,\ldots,4$ of the model parameters were obtained. However, not all the parameters in the model are linearly independent since the constraint

$$\sum_{h=1}^{4} \lambda_h^r = \sum_{j=1}^{4} \lambda_j^c = 0$$

is required in this kind of modeling in order to make the parameters identifiable (Agresti, 1990). As a result, it was taken $\lambda_1^h = \lambda_1^c = 0$, which simplifies the model.

To ease the computations, from now on, matrix notation will be used. The linearly independent parameters in the model are 12 (λ, λ_2^r, λ_3^r, λ_4^r, λ_2^c, λ_3^c, λ_4^c, β, δ_1, δ_2, δ_3, δ_4) and they constitute the parameter vector $\boldsymbol{\theta}$. Thus, for instance $\theta_4 = \lambda_4^r$. The corresponding maximum likelihood estimators of the parameters constitute the vector $\hat{\boldsymbol{\theta}}$. Moreover, $\boldsymbol{n}$, $\boldsymbol{m}$ and $\boldsymbol{w}$ are, respectively, the vectors of observed frequencies, expected frequencies and the logarithms of expected frequencies ordered according to the indices $l = 4h + j - 4$. In Table 4 is presented the correspondence between the expected frequencies indexed by l and the expected frequencies in the contingency table. This correspondence needs to be known because it is required to relate the results for the frequencies with the corresponding drought class transition, which is given by their position in the contingency table. The model matrix, containing known constants derived from Eq. (1), takes the form

$$\mathbf{X} = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 2 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 1 & 0 & 3 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 1 & 4 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 & 0 & 2 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 1 & 0 & 0 & 4 & 0 & 1 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 1 & 0 & 6 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 & 1 & 8 & 0 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 1 & 0 & 0 & 6 & 0 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 0 & 1 & 0 & 9 & 0 & 0 & 1 & 0 \\
1 & 0 & 1 & 0 & 0 & 0 & 1 & 12 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 0 & 0 & 0 & 4 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 1 & 0 & 0 & 8 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 0 & 1 & 0 & 12 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 0 & 0 & 1 & 16 & 0 & 0 & 0 & 1
\end{bmatrix}.$$

Let designate the 12 components row vectors of $\mathbf{X}$ by $\mathbf{x}_t$ with $t = 1,\ldots,16$. This matrix $\mathbf{X}$ is the same for all stations because it relates with the QA loglinear model and does not depend on the data set. The QA loglinear model in matrix notation is then

$$\boldsymbol{w} = \log \boldsymbol{m} = \mathbf{X}\boldsymbol{\theta}. \tag{2}$$

Since a rather long time span is used, it may be assumed that:

- the vector $\hat{\boldsymbol{\theta}}$ of MLE estimates is asymptotically normal with mean value $\boldsymbol{\theta}$ and variance-covariance matrix

  $$(\mathbf{X}^T \mathbf{D}(\hat{\mathbf{m}})\mathbf{X})^{-1} \tag{3}$$

  (Agresti, 1990), where $\mathbf{D}(\hat{\mathbf{m}})$ is the diagonal matrix, whose principal elements are the adjusted expected frequencies;

- the vector $\hat{\boldsymbol{\theta}}$ is independent from the residual deviance

  $$G^2 = 2\sum_{l=1}^{16} n_l \log(n_l/\hat{m}_l) = 2\left(\sum_{l=1}^{16} n_l \log(n_l) - \sum_{l=1}^{16} n_l \hat{w}_l\right) \tag{4}$$

  which is asymptotically distributed as a central Chi-Square with four degrees of freedom since there are 16 cells in the contingency tables and 12 linearly independent parameters to be adjusted (Agresti, 1990; Nelder, 1974). In the expression of G^2 the frequencies were ordered according to index l.

Therefore, to validate the adjustment of the model, the Chi-Square test may used with statistic G^2 (Agresti, 1990; Nelder, 1974). Table 5 presents the adjusted parameters and the residual deviances for all stations and respective sub-periods.

An analysis of variance was applied following this modeling aiming at finding significant differences between the sub-periods of each time series. The logarithms of the expected number of transitions between all drought classes were taken as observations in an one-way ANOVA linear model with fixed effects (Hocking, 2003). In this ANOVA application, each expected frequency obtained from fitting a loglinear model to a contingency table relative to every sub-period, was compared with the same expected frequency of another sub-period of the same time series.

In order to perform ANOVA to compare the expected frequencies generated by the different loglinear models, some ANOVA algorithms had to be adapted as presented in Appendix A.

4 Results and discussion

The F test was applied to all drought class transitions and the results obtained are presented in Table 6 for the transitions that present significant differences between the sub-periods. Those results allow concluding that, in general, there are significant differences between the 5 or 4 sub-periods of each time series for the transitions $m_{1,1}$, $m_{2,2}$, $m_{3,3}$, $m_{4,4}$, $m_{3,4}$, $m_{4,2}$, $m_{3,2}$ and $m_{2,3}$. Differently, the remaining transitions did not show significant differences.

The transitions $m_{1,1}$, $m_{2,2}$, $m_{3,3}$ and $m_{4,4}$ between each drought class and themselves, are the most important for the analysis in the sense that they indicate the persistence of these drought classes. In particular, the transition $m_{4,4}$, referring to the persistence of the severe/extreme drought class, and the $m_{3,4}$, referring to the transition from moderate to the severe/extreme drought class, are of special interest, because this study aims to detect if droughts severity and frequency are increasing.

The Scheffé multiple comparison method was applied for the transitions that presented significant differences, whose results are presented in Tables 7 and 8. With this method, each combination of pairs of sub-periods was tested in order to find significant differences between 2 sub-periods for each drought transition $m_{h,j}$, $h,j = 1,2,3,4$. In Tables 7 and 8, the word "yes" is used to indicate when there is significant differences between h & j sub-periods and "no" otherwise. Table 9 presents the pattern of what

should be the typical behavior of a cycle of more or less severe droughts in opposition to a trend of progressive drought increase during the last century. When there is a cycle, there is similarity between alternating sub-periods and significant differences between consecutive sub-periods. Differently, if there is a trend, linear or non-linear, then significant differences must exist between consecutive sub-periods.

In the present study long time series were analyzed. Three of them are from the north of Portugal and the others are from south. Analyzing the results of the first ones (Table 7 and Fig. 2), Montalegre presents a situation of increased occurrence of droughts from the 1st to the 3rd sub-period, a decrease from the 3rd to the 4th sub-period, and a maintenance from 4th to the 5th. Overall, there is no evidence of drought aggravation for the period of 127 yr of observations. This behavior does not fit in any typical pattern. That behavior is different from the southern locations and may relate to the fact that local climate is humid, with the site elevation (1069 m) influencing the precipitation regime.

Porto-Serra do Pilar (Table 7 and Fig. 2) shows a non-typical behavior: during the first three sub-periods there is no evidence of changes in drought frequency and severity, while, from the 3rd to the 4th sub-periods there is a significant decrease of droughts occurrence and severity followed by a non-significant increase from the 4th to the 5th sub-periods. Thus, results do not show aggravation of drought for the last 135 yr. To be noted that Porto is near the Atlantic Ocean and has a sub-humid to humid climate.

Penhas Douradas (Table 7 and Fig. 2) shows a significant increase of the occurrence of severe/extreme droughts in the last sub-period in opposition to a maintenance of drought severity for the 4 antecedent sub-periods. Penhas Douradas has a humid climate and is located at 1380 m elevation; the significant increase in occurrence of severe/extreme droughts in the last 27 yr may be due to different factors other than global climate change.

In the South (Table 8 and Figs. 2 and 3) a more consistent behavior can be found. Some sites, such as Pavia, Beja, Chouto and S. B. Alportel, relative to the occurrence of severe/extreme droughts and moderate droughts, show a behavior typical of a cycle: there is similarity between alternating sub-periods and significant differences between consecutive ones. The sub-periods with few severe/extreme droughts are followed by sub-periods of higher frequency and persistence of severe/extreme drought.

Lisboa (Table 7 and Fig. 3), if just considering the sub-periods 2, 3, 4 and 5, shows also a typical cyclic behavior, which is not observed for the pair of the 1st and 2nd sub-periods. However, there is no evidence of significant decrease of severe/extreme droughts between sub-periods 1 and 2; results for Lisboa show a behavior that is closer to a cycle than to a trend for increase of droughts severity and frequency.

Évora (Table 7 and Fig. 3), in the middle of the drought prone Alentejo, seems to behave like an outlier in the sense that it would be expected that the sub-period 3 would have more severe/extreme droughts but, instead, this sub-period does not differ significatively from the 2nd and the 4th. The 1st sub-period shows to have a larger number of drought events, hence differing significatively from the following sub-periods. However, the occurrence and severity of droughts also increase significantly in 5th sub-period relative to the precedent sub-periods, including relative to the 1th one. Therefore, this station does not show neither a clear long term trend for drought aggravation, or a cyclic behavior; nevertheless, droughts are aggravating in the last 27 yr of the considered period of 135 yr.

Faro (Table 8 and Fig. 3) only shows a significant increase in severe/extreme droughts between the 4th and the 5th sub-periods, but not between the other 2 sub-periods and the 5th. Thus, results for this location can not be interpreted as indicating a cyclic behavior of droughts occurrence and severity, neither expressing a trend.

The results of a previous study (Moreira et al., 2006), where time series with 67 yr were studied relative to various locations in Alentejo (southern Portugal), pointed to a cyclic behavior that could be related with a possible long-term natural variability. These results needed to be corroborated with a further study using longer time series. In the present paper, 10 long time series, with 95 to 135 yr, from different regions of Portugal were divided into 5 or 4 sub-periods, in the expectance of existing similarity, for instance, between the 1st, 3rd and 5th sub-periods, all having significant high

occurrence of severe/extreme drought occurrence. The results, however, show to be different among locations studied. For the northern part of the country, where locations have an humid climate and data sets are longer than 127 yr, that cyclic behavior was not found. Porto and Montalegre also do not show trends for droughts aggravation but Penhas Douradas show an aggravation of droughts for the last sub-period. For the South, cases of Lisboa, Pavia, Chouto, Beja and S. B. Alportel, results show a behavior generally consistent with a cyclic occurrence and severity of droughts. However, other stations of southern Portugal – Évora and Faro – show a significant aggravation of droughts for the 5th period only. Because these results are in contradiction with those of other locations within the same region, it is not possible to relate this aggravation of droughts to climate change. Hence, there is a possibility that droughts behavior in the Alentejo region may be to due long-term natural variability.

5 Conclusions

ANOVA-like inference together with loglinear models have shown high potentialities to compare drought class transitions among different sub-periods. The methodology revealed to be robust and very sensitive in detecting variability. In this study, ANOVA is a new approach that can be used as an alternative to the Odds ratios and correspondent confidence intervals, as used in a former analysis with loglinear models.

In the Southern region, results for the sites of Pavia, Beja, Chouto, S. B. Alportel and Lisboa have shown that droughts occurrence and severity behave in a cyclic way, in which a sub-period with few severe/extreme droughts is followed by a sub-period of higher frequency of severe/extreme droughts. This cycle may be related to a long-term natural variability, with the duration of the sub-periods ranging from 26 to 30 yr. For the other locations, mainly those from North, there is no evidence of a typical cyclic behavior, neither a trend for drought aggravation. Therefore, globally, the results do not support the assumption of a trend of drought aggravation since the beginning of the twenty century that could be related with climate change. Nevertheless, if comparing the last period of 27 yr with the precedent one of 24, in general there is a significant increasing of droughts occurrence and severity with exception of Montalegre and Porto in the north. Results also point out the need for using long time series.

Appendix A

One-way ANOVA-like inference and Scheff multiple comparison

Following Sect. 3

$$\hat{w}_l = \mathbf{x}_l^T \hat{\boldsymbol{\theta}}, l = 1, \ldots, 16 \quad \text{(A1)}$$

is also normal with mean value w_l and variance

$$V(\hat{w}_l) = \mathbf{x}_l^T (\mathbf{X}^T \mathbf{D}(\hat{\boldsymbol{m}})\mathbf{X})^{-1} \mathbf{x}_l. \quad \text{(A2)}$$

Thus, an ANOVA-like inference can be used to compare the expected frequencies between the sub-periods of the same time series, since the normality of the response variable (the logarithms of the expected frequencies) can be assumed.

ANOVA-like inference was performed for each time series. Supposing a time series divided into 5 sub-periods, these 5 were considered as treatments of one-way ANOVA (Montgomery, 1997). For easiness of the computation and presentation, the ANOVA technique is presented following a matrix formulation.

Let the 5 sub-periods be indexed by $i = 1, \ldots, 5$, so the vectors $\boldsymbol{n}_i$, $\hat{\boldsymbol{m}}_i$ and $\hat{\boldsymbol{w}}_i$ can be defined, as well as a matrix

$$\mathbf{Y} = [\hat{\boldsymbol{w}}_\mathbf{1} \ldots \hat{\boldsymbol{w}}_\mathbf{5}]^\mathbf{T} \quad \text{(A3)}$$

with row vectors $\boldsymbol{y}_l = [\hat{w}_{l,1} \ldots \hat{w}_{l,5}]$, having mean vectors $\boldsymbol{\mu}_l = [w_{l,1} \ldots w_{l,5}]$, $l = 1, \ldots, 16$. If the 5 sub-periods are similar, the hypothesis

$$H_{0,l} : w_{l,1} = \ldots = w_{l,5}, l = 1, \ldots, 16 \quad \text{(A4)}$$

will hold. This hypothesis may be rewritten as

$$H_{0,l} : \mathbf{A}\boldsymbol{\mu}_l = \mathbf{0}, l = 1, \ldots, 16 \quad \text{(A5)}$$

where the matrix $\mathbf{A}$ has, for instance, the following configuration

$$\mathbf{A} = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ 1 & 0 & -1 & 0 & 0 \\ 1 & 0 & 0 & -1 & 0 \\ 1 & 0 & 0 & 0 & -1 \end{bmatrix}$$

that serves to correctly formulate the hypothesis of equality between the mean values $w_{l,i}, l = 1, \ldots, 16, i = 1, \ldots, 5$. Vectors $\boldsymbol{y}_l$ are normal with mean vectors $\boldsymbol{\mu}_l$ and diagonal variance-covariance matrices, $\mathbf{D}_l$, with principal elements $\mathbf{x}_l^T (\mathbf{X}^T \mathbf{D}(\hat{\boldsymbol{m}}_1)\mathbf{X})^{-1} \mathbf{x}_l$,..., $\mathbf{x}_l^T (\mathbf{X}^T \mathbf{D}(\hat{\boldsymbol{m}}_5)\mathbf{X})^{-1} \mathbf{x}_l$, $l = 1, \ldots, 16$, independent from

$$\mathrm{SG}^2 = \sum_{i=1}^{5} G_i^2 \quad \text{(A6)}$$

which is asymptotically distributed as a central chi-square with 20 degrees of freedom (Scheffé, 1959). Thus, $\mathbf{A}\boldsymbol{y}_l$ is also normal with mean vector $\mathbf{A}\boldsymbol{\mu}_l$ and variance-covariance matrix $\mathbf{A}\mathbf{D}_l\mathbf{A}^T$, $l = 1, \ldots, 16$. Therefore, when $H_{0,t}$, $l = 1, \ldots, 16$ holds, the statistics

$$\mathcal{F}_l = \frac{12}{2} \frac{(\mathbf{A}\boldsymbol{y}_l)^T (\mathbf{A}\mathbf{D}_l\mathbf{A}^T)^{-1} \mathbf{A}\boldsymbol{y}_l}{\mathrm{SG}^2}, l = 1, \ldots, 16 \quad \text{(A7)}$$

will have a central F distribution with 4 and 20 degrees of freedom (Scheffé, 1959). The null hypothesis is rejected if the value of the $\mathcal{F}_l$ statistic exceeds the 5 % quantil for an F distribution with 4 and 20 degrees of freedom ($F_{0.05,4,20}$).

When the time series were divided into 4 sub-periods, the vectors $\boldsymbol{y}_l$ and $\boldsymbol{\mu}_l$ have only with 4 components, a matrix

$$\mathbf{A} = \begin{bmatrix} 1 & -1 & 0 & 0 \\ 1 & 0 & -1 & 0 \\ 1 & 0 & 0 & -1 \end{bmatrix}$$

is used and the $\mathcal{F}_l$ statistic have central F distribution with 3 an 16 degrees of freedom.

In order to find if there are significant differences between sub-period pairs, the Scheffé multiple comparison method is used.

As a consequence of Scheffé theorem (Scheffé, 1959), if the inequality

$$|\mathbf{d}^T \mathbf{y}_l| > \sqrt{\frac{4}{20}F_{0.05,4,20}\mathbf{d}^T(\mathbf{D}_l)^{-1}\mathbf{d}\mathrm{SG}^2}, l = 1, \ldots, 16$$

occurs, then the sub-periods

- 1 and 2 are significantly different if considering a vector

  $\mathbf{d}^T = [1 - 1\,0\,0\,0]$;

- 1 and 3 are significantly different if considering a vector

  $\mathbf{d}^T = [1\,0 - 1\,0\,0]$;

- ...

- 3 and 4 are significantly different if considering a vector

  $\mathbf{d}^T = [0\,0\,0\,1 - 1]$.

Thus, just for the cases that presented significant differences in the F test, it can be found between which combination of sub-periods pairs there are significant differences (combinations of 5 sub-periods two by two, 10 in total or combinations of 4 two by two, 6 in total).

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Table 1. Drought classification of SPI (modified from Mckee et al., 1993).

Code	Drought classes	SPI values
1	Non-drought	SPI ≥ 0
2	Near normal	−1 < SPI < 0
3	Moderate	−1.5 < SPI ≤ −1
4	Severe/Extreme	SPI ≤ −1.5

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

Table 2. Division into 4 or 5 sub-periods according to each time series total duration.

	Montalegre		Porto-Serra Pilar		Penhas Douradas		Pavia, Chouto	
Period	Year	Size (years)	Year	Size (years)	Year	Size (years)	Year	Size (years)
	1880		1872		1883			
1st	1900	20	1900	28	1900	17	1912	
2nd	1926	26	1926	26	1926	26	1926	14
3rd	1956	30	1956	30	1956	30	1956	30
4th	1980	24	1980	24	1980	24	1980	24
5th	2007	27	2007	27	2007	27	2007	27
Total		127		135		124		95
	Lisboa, Évora		S. B. Alportel		Beja, Faro			
Period	Year	Size(years)	Year	Size(year)	Year	Size(years)		
	1872							
1st	1900	28	1910		1900			
2nd	1926	26	1926	16	1926	26		
3rd	1956	30	1956	30	1956	30		
4th	1980	24	1980	24	1980	24		
5th	2007	27	2007	27	2007	27		
Total		135		97		107		

Table 3. Contingency tables resulting from the division of the Porto time series into 5 sub-periods.

	1st period Drought class $t+1$				2nd period Drought class $t+1$				3rd period Drought class $t+1$				4th period Drought class $t+1$				5th period Drought class $t+1$			
Drought class month t	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	163	16	0	0	121	24	0	0	139	15	0	0	195	12	0	0	141	24	0	0
2	16	101	14	0	23	111	13	2	15	93	11	3	14	102	8	1	23	103	9	1
3	1	13	19	5	1	15	22	3	1	11	30	5	1	8	12	2	1	8	30	4
4	0	1	4	8	0	0	6	20	0	3	5	30	0	0	2	4	0	0	4	11

Table 4. Correspondence between the expected frequencies $m_{hj}, h, j = 1, 2, 3, 4$ and the same expected frequencies indexed by $t = 1, \ldots, 16$.

m_t	m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}	m_{11}	m_{12}	m_{13}	m_{14}	m_{15}	m_{16}
$m_{h,j}$	$m_{1,1}$	$m_{1,2}$	$m_{1,3}$	$m_{1,4}$	$m_{2,1}$	$m_{2,2}$	$m_{2,3}$	$m_{2,4}$	$m_{3,1}$	$m_{3,2}$	$m_{3,3}$	$m_{3,4}$	$m_{4,1}$	$m_{4,2}$	$m_{4,3}$	$m_{4,4}$

Table 5. Estimates of QA loglinear model parameters fitted to contingency tables and correspondent residual deviances for the 10 sites by sub-period.

	Montalegre	Porto	Penhas	Pavia	Chouto	Lisboa	Évora	Beja	SBAlportel	Faro
					1st sub-period					
λ	1.008	1.361	0.785			1.974	1.337			
λ_2^r	−1.780	−2.350	−1.320			−2.518	−2.100			
λ_3^r	−6.460	−7.680	−4.790			−7.970	−7.310			
λ_4^r	−12.650	−14.770	−8.960			−13.630	−13.260			
λ_2^c	−2.040	−2.400	−1.140			−2.564	−2.100			
λ_3^c	−6.880	−7.810	−4.980			−8.120	−7.310			
λ_4^c	−13.330	−14.890	−9.720			−13.760	−13.260			
β	1.645	1.893	1.117			1.781	1.752			
δ_1	2.199	1.840	3.740			1.465	1.999			
δ_2	1.212	0.431	1.140			0.217	0.298			
δ_3	0.859	0.030	0.870			1.335	0.598			
δ_4	0.840	0.090	0.030			−0.594	0.201			
G^2	2.301	2.869	2.446			1.352	1.492			
					2nd sub-period					
	Montalegre	Porto	Penhas	Pavia	Chouto	Lisboa	Évora	Beja	SBAlportel	Faro
λ	1.851	1.603	1.584	1.660	2.205	2.215	1.081	1.422	1.738	0.623
λ_2^r	−2.547	−2.033	−1.860	−1.450	−2.120	−2.550	−0.640	−0.430	−0.080	−0.726
λ_3^r	−8.350	−7.670	−6.700	−7.160	−7.420	−8.170	−5.620	−5.300	−4.360	−5.570
λ_4^r	−14.820	−13.820	−12.310	−13.410	−12.430	−14.380	−10.500	−9.280	−7.170	−10.440
λ_2^c	−2.587	−2.032	−1.990	−1.480	−2.170	−2.590	−0.540	−0.510	−0.080	−0.789
λ_3^c	−8.450	−7.720	−6.950	−7.170	−7.400	−8.400	−5.440	−5.540	−4.360	−5.670
λ_4^c	−14.920	−14.050	−12.540	−14.120	−13.130	−14.980	−10.360	−10.110	−7.170	−10.680
β	1.947	1.794	1.506	1.601	1.494	1.786	1.240	1.082	0.819	1.422
δ_1	0.865	1.400	2.198	1.169	1.471	1.135	2.690	2.608	2.362	1.945
δ_2	0.140	−0.002	0.825	−0.036	0.937	0.460	−0.030	0.000	−0.069	0.360
δ_3	0.473	0.731	0.997	1.440	0.960	0.078	1.594	1.772	2.661	1.514
δ_4	0.396	0.561	0.960	0.250	−0.540	0.180	0.620	0.670	−0.510	0.521
G^2	1.354	5.253	3.065	2.570	2.846	2.393	1.713	2.423	6.840	3.515
					3tr sub−period					
	Montalegre	Porto	Penhas	Pavia	Chouto	Lisboa	Évora	Beja	SBAlportel	Faro
λ	0.911	0.863	2.051	1.054	1.118	1.667	1.283	1.120	1.371	1.518
λ_2^r	−0.428	−0.804	−2.550	−1.400	−1.965	−2.056	−1.128	−1.076	−1.594	−2.490
λ_3^r	−3.920	−5.600	−8.110	−6.420	−6.680	−7.490	−5.110	−6.100	−6.670	−7.900
λ_4^r	−7.100	−9.610	−14.580	−11.680	−12.190	−11.810	−10.320	−9.860	−10.420	−14.960
λ_2^c	−0.428	−0.867	−2.600	−1.457	−2.048	−2.056	−1.192	−1.131	−1.652	−2.540
λ_3^c	−3.920	−5.740	−8.260	−6.590	−6.860	−7.490	−5.170	−6.230	−6.810	−8.030
λ_4^c	−7.100	−9.720	−14.710	−11.980	−12.350	−11.810	−10.380	−9.960	−10.540	−15.080
β	0.958	1.340	1.808	1.574	1.643	1.680	1.275	1.408	1.512	1.914
δ_1	2.849	2.731	1.185	2.328	2.375	1.505	2.678	2.462	2.036	1.611
δ_2	0.954	−0.020	0.523	−0.121	0.614	0.191	0.389	−0.070	0.389	0.507
δ_3	1.080	1.814	1.446	0.925	0.858	1.594	0.148	1.662	1.895	−0.109
δ_4	1.837	0.425	−0.590	1.182	0.744	−1.708	0.624	−0.572	−1.570	0.667
G^2	0.430	1.457	2.979	5.938	1.341	1.958	0.080	2.500	2.479	2.872

Table 5. Continued.

4th sub−period										
	Montalegre	Porto	Penhas	Pavia	Chouto	Lisboa	Évora	Beja	SBAlportel	Faro
λ	2.246	1.322	0.421	3.023	2.256	0.987	0.990	1.617	1.345	0.706
λ_2^r	−2.290	−1.770	−0.960	−3.150	−2.310	−0.953	−1.592	−0.966	−2.400	−0.575
λ_3^r	−7.230	−6.600	−5.630	−8.140	−7.200	−5.090	−6.280	−4.680	−7.260	−4.550
λ_4^r	−12.110	−12.730	−12.120	−12.550	−11.530	−8.330	−11.590	−9.000	−13.510	−7.810
λ_2^c	−2.330	−1.990	−1.040	−3.190	−2.370	−1.030	−1.592	−0.966	−2.400	−0.575
λ_3^c	−7.630	−6.830	−5.800	−8.790	−7.170	−5.550	−6.280	−4.680	−7.350	−4.550
λ_4^c	−13.080	−12.560	−12.680	−13.700	−12.220	−8.850	−11.590	−9.000	−13.810	−7.810
β	1.478	1.560	1.531	1.545	1.396	1.154	1.522	1.056	1.750	1.006
δ_1	1.780	2.392	3.097	0.840	1.830	3.116	2.786	2.665	2.252	3.765
δ_2	0.576	0.829	0.116	1.677	1.209	1.044	0.615	0.485	0.949	0.685
δ_3	1.610	0.561	0.328	0.000	0.940	2.036	0.576	0.319	−0.091	1.733
δ_4	−0.710	0.400	2.180	−1.500	−0.840	−0.070	−2.160	−0.520	−2.020	0.210
G^2	2.179	2.416	2.461	2.017	3.143	8.857	1.528	9.058	2.742	2.733
5th sub−period										
	Montalegre	Porto	Penhas	Pavia	Chouto	Lisboa	Évora	Beja	SBAlportel	Faro
λ	1.605	2.299	1.134	2.030	1.655	1.481	1.105	1.578	1.926	2.579
λ_2^r	−1.620	−3.110	−2.830	−3.080	−2.510	−1.434	−1.466	−1.142	−2.632	−2.939
λ_3^r	−6.510	−9.010	−8.250	−8.710	−8.140	−6.760	−6.380	−6.380	−7.000	−7.370
λ_4^r	−11.810	−15.940	−16.160	−15.680	−15.220	−10.210	−10.440	−9.740	−12.770	−11.700
λ_2^c	−1.670	−3.120	−2.820	−3.030	−2.510	−1.436	−1.532	−1.142	−2.567	−2.886
λ_3^c	−6.770	−8.920	−8.300	−8.670	−8.200	−6.710	−6.520	−6.380	−6.940	−7.180
λ_4^c	−12.700	−15.640	−16.200	−15.460	−15.490	−10.100	−10.560	−9.740	−12.710	−11.530
β	1.437	1.986	2.147	1.987	1.937	1.463	1.517	1.316	1.674	1.538
δ_1	2.342	0.664	0.796	1.059	1.244	2.005	2.097	1.988	1.424	1.025
δ_2	0.428	0.620	0.716	0.641	0.296	−0.055	0.422	−0.016	0.922	1.562
δ_3	0.690	1.151	−0.197	0.568	0.741	1.599	0.982	1.128	0.282	0.769
δ_4	−0.090	−0.100	0.811	0.321	0.700	−0.909	−0.344	0.821	0.103	−0.774
G^2	2.265	2.715	2.861	3.401	2.706	2.089	1.714	1.947	3.300	4.018

Table 6. Results of the F tests.

	$\mathbf{m}_{4,4}$			$\mathbf{m}_{3,3}$			$\mathbf{m}_{2,2}$			$\mathbf{m}_{1,1}$		
Time series	$\mathcal{F}$		5% F	$\mathcal{F}$		5% F	$\mathcal{F}$		5 % F	$\mathcal{F}$		5 % F
MONTALEGRE	38.237	>	2.866	12.767	>	2.866	31.405	>	2.866	80.423	>	2.866
PORTO	9.825	>	2.866	3.300	>	2.866	0.565	<	2.866	7.144	>	2.866
PENHAS	25.210	>	2.866	10.461	>	2.866	10.021	>	2.866	49.752	>	2.866
CHOUTO	16.502	>	3.239	14.522	>	3.239	9.706	>	3.239	19.405	>	3.239
PAVIA	12.221	>	3.239	3.753	>	3.239	15.393	>	3.239	23.658	>	3.239
LISBOA	10.766	>	2.866	4.981	>	2.866	3.571	>	2.866	5.606	>	2.866
EVORA	50.686	>	2.866	1.746	<	2.866	8.682	>	2.866	22.002	>	2.866
BEJA	12.166	>	3.239	4.840	>	3.239	3.470	>	3.239	6.627	>	3.239
S.B.ALPORTEL	7.232	>	3.239	3.189	<	3.239	3.459	>	3.239	7.823	>	3.239
FARO	4.610	>	3.239	10.065	>	3.239	21.582	>	3.239	40.592	>	3.239
	$\mathbf{m}_{3,4}$			$\mathbf{m}_{4,2}$			$\mathbf{m}_{3,2}$			$\mathbf{m}_{2,3}$		
Time series	$\mathcal{F}$		5% F	$\mathcal{F}$		5% F	$\mathcal{F}$		5% F	$\mathcal{F}$		5% F
MONTALEGRE	6.505	>	2.866	4.915	>	2.866	3.712	>	2.866	4.988	>	2.866
PORTO	0.355	<	2.866	0.692	<	2.866	1.166	<	2.866	0.779	<	2.866
PENHAS	6.284	>	2.866	5.697	>	2.866	5.400	>	2.866	5.657	>	2.866
CHOUTO	3.482	>	3.239	2.430	<	3.239	4.688	>	3.239	3.834	>	3.239
PAVIA	2.259	<	3.239	1.605	<	3.239	2.994	<	3.239	3.301	>	3.239
LISBOA	3.820	>	2.866	3.451	>	2.866	0.242	<	2.866	0.665	<	2.866
EVORA	8.093	>	2.866	7.787	>	2.866	0.893	<	2.866	1.075	<	2.866
BEJA	2.529	<	3.239	2.182	<	3.239	0.307	<	3.239	0.345	<	3.239
S.B.ALPORTEL	3.526	>	3.239	3.205	<	3.239	0.170	<	3.239	0.276	<	3.239
FARO	2.187	<	3.239	2.182	<	3.239	4.278	>	3.239	3.556	>	3.239

Table 7. Results for the pairwise comparison of sub-periods (Scheffé multiple comparison method). "yes" is used to indicate when there is significant differences between *h* & *j* sub-periods and "no" otherwise.

Montalegre		Porto		Penhas Douradas		Lisboa		Evora	
				$m_{4,4}$					
1 & 2	yes	1 & 2	no	1 & 2	no	1 & 2	no	1 & 2	yes
1 & 3	yes	1 & 3	yes	1 & 3	no	1 & 3	no	1 & 3	yes
1 & 4	yes	1 & 4	no	1 & 4	no	1 & 4	no	1 & 4	yes
1 & 5	yes	1 & 5	no	1 & 5	yes	1 & 5	yes	1 & 5	yes
2 & 3	no	2 & 3	no	2 & 3	no	2 & 3	yes	2 & 3	no
2 & 4	yes	2 & 4	yes	2 & 4	no	2 & 4	no	2 & 4	no
2 & 5	yes	2 & 5	no	2 & 5	yes	2 & 5	yes	2 & 5	yes
3 & 4	yes	3 & 4	yes	3 & 4	no	3 & 4	yes	3 & 4	no
3 & 5	yes	3 & 5	yes	3 & 5	yes	3 & 5	no	3 & 5	yes
4 & 5	no	4 & 5	no	4 & 5	yes	4 & 5	yes	4 & 5	yes
				$m_{3,3}$					
1 & 2	no	1 & 2	no	1 & 2	no	1 & 2	yes	1 & 2	no
1 & 3	no	1 & 3	no	1 & 3	yes	1 & 3	no	1 & 3	no
1 & 4	yes	1 & 4	no	1 & 4	no	1 & 4	no	1 & 4	no
1 & 5	yes	1 & 5	no	1 & 5	yes	1 & 5	no	1 & 5	no
2 & 3	no	2 & 3	no	2 & 3	no	2 & 3	yes	2 & 3	no
2 & 4	yes	2 & 4	no	2 & 4	no	2 & 4	no	2 & 4	no
2 & 5	yes	2 & 5	no	2 & 5	yes	2 & 5	no	2 & 5	no
3 & 4	no	3 & 4	yes	3 & 4	no	3 & 4	no	3 & 4	no
3 & 5	no	3 & 5	no	3 & 5	no	3 & 5	no	3 & 5	no
4 & 5	no	4 & 5	yes	4 & 5	no	4 & 5	no	4 & 5	no
				$m_{2,2}$					
1 & 2	yes	1 & 2	no	1 & 2	yes	1 & 2	yes	1 & 2	yes
1 & 3	no	1 & 3	no	1 & 3	yes	1 & 3	no	1 & 3	no
1 & 4	yes	1 & 4	no	1 & 4	yes	1 & 4	no	1 & 4	no
1 & 5	yes	1 & 5	no	1 & 5	yes	1 & 5	no	1 & 5	no
2 & 3	no	2 & 3	no	2 & 3	no	2 & 3	no	2 & 3	yes
2 & 4	yes	2 & 4	no	2 & 4	no	2 & 4	no	2 & 4	yes
2 & 5	no	2 & 5	no	2 & 5	no	2 & 5	no	2 & 5	no
3 & 4	yes	3 & 4	no	3 & 4	no	3 & 4	no	3 & 4	no
3 & 5	yes	3 & 5	no	3 & 5	no	3 & 5	no	3 & 5	no
4 & 5	yes	4 & 5	no	4 & 5	no	4 & 5	no	4 & 5	no

Table 7. Continued.

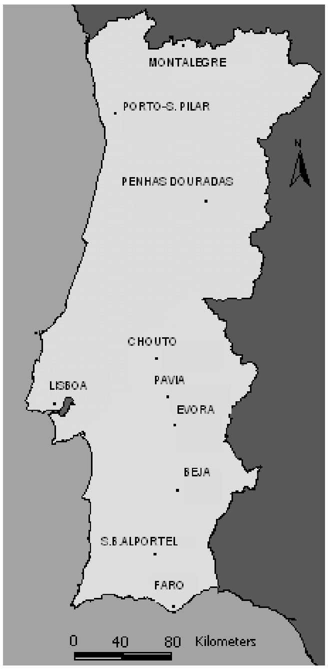
Montalegre		Porto		Penhas Douradas		Lisboa		Evora	
				$m_{1,1}$					
1 & 2	no	1 & 2	no	1 & 2	yes	1 & 2	no	1 & 2	no
1 & 3	no	1 & 3	no	1 & 3	yes	1 & 3	yes	1 & 3	no
1 & 4	yes	1 & 4	no	1 & 4	yes	1 & 4	no	1 & 4	yes
1 & 5	yes	1 & 5	no	1 & 5	yes	1 & 5	no	1 & 5	yes
2 & 3	no	2 & 3	no	2 & 3	no	2 & 3	no	2 & 3	yes
2 & 4	yes	2 & 4	yes	2 & 4	no	2 & 4	no	2 & 4	yes
2 & 5	yes	2 & 5	no	2 & 5	yes	2 & 5	no	2 & 5	yes
3 & 4	yes	3 & 4	yes	3 & 4	no	3 & 4	yes	3 & 4	no
3 & 5	yes	3 & 5	no	3 & 5	yes	3 & 5	no	3 & 5	yes
4 & 5	no	4 & 5	yes	4 & 5	yes	4 & 5	no	4 & 5	yes
				$m_{3,4}$					
1& 2	yes	1 & 2	no	1 & 2	no	1& 2	no	1& 2	yes
1& 3	no	1& 3	no	1& 3	no	1& 3	no	1& 3	no
1& 4	no	1& 4	no	1& 4	no	1& 4	no	1& 4	no
1& 5	no	1& 5	no	1& 5	yes	1& 5	no	1& 5	no
2& 3	no	2& 3	no	2& 3	no	2& 3	yes	2& 3	no
2& 4	yes	2& 4	no	2& 4	no	2& 4	no	2& 4	no
2& 5	yes	2& 5	no	2& 5	yes	2& 5	no	2& 5	yes
3& 4	yes	3& 4	no	3& 4	no	3& 4	yes	3& 4	no
3& 5	yes	3& 5	no	3& 5	no	3& 5	no	3& 5	yes
4& 5	no	4& 5	no	4& 5	yes	4& 5	no	4& 5	yes

Table 8. Results for the pairwise comparison of sub-periods. "yes" is used to indicate when there is significant differences between *h* & *j* sub-periods and "no" otherwise (cont.).

Pavia		Chouto		Beja		S.B.Alportel		Faro	
				$m_{4,4}$					
2 & 3	yes	2 & 3	yes	2 & 3	yes	2 & 3	yes	2 & 3	no
2 & 4	no	2 & 4	no	2 & 4	no	2 & 4	no	2 & 4	no
2 & 5	yes	2 & 5	yes	2 & 5	yes	2 & 5	yes	2 & 5	no
3 & 4	yes	3 & 4	yes	3 & 4	yes	3 & 4	yes	3 & 4	no
3 & 5	no	3 & 5	yes	3 & 5	no	3 & 5	no	3 & 5	no
4 & 5	yes	4 & 5	yes	4 & 5	yes	4 & 5	yes	4 & 5	yes
				$m_{3,3}$					
2 & 3	no	2 & 3	yes	2 & 3	no	2 & 3	no	2 & 3	yes
2 & 4	yes	2 & 4	no	2 & 4	no	2 & 4	no	2 & 4	yes
2 & 5	no	2 & 5	yes	2 & 5	no	2 & 5	no	2 & 5	yes
3 & 4	yes	3 & 4	yes	3 & 4	no	3 & 4	no	3 & 4	no
3 & 5	no	3 & 5	no	3 & 5	no	3 & 5	no	3 & 5	no
4 & 5	yes	4 & 5	yes	4 & 5	no	4 & 5	no	4 & 5	no
				$m_{2,2}$					
2 & 3	yes	2 & 3	yes	2 & 3	no	2 & 3	no	2 & 3	yes
2 & 4	yes	2 & 4	yes	2 & 4	no	2 & 4	no	2 & 4	yes
2 & 5	yes	2 & 5	no	2 & 5	no	2 & 5	yes	2 & 5	yes
3 & 4	no	3 & 4	no	3 & 4	no	3 & 4	no	3 & 4	no
3 & 5	no	3 & 5	yes	3 & 5	no	3 & 5	no	3 & 5	no
4 & 5	no	4 & 5	no	4 & 5	no	4 & 5	no	4 & 5	no
				$m_{1,1}$					
2 & 3	yes	2 & 3	no	2 & 3	no	2 & 3	no	2 & 3	yes
2 & 4	yes	2 & 4	yes	2 & 4	no	2 & 4	yes	2 & 4	yes
2 & 5	yes	2 & 5	yes	2 & 5	no	2 & 5	no	2 & 5	yes
3 & 4	yes	3 & 4	yes	3 & 4	yes	3 & 4	yes	3 & 4	yes
3 & 5	no	3 & 5	yes	3 & 5	no	3 & 5	no	3 & 5	no
4 & 5	yes	4 & 5	yes	4 & 5	yes	4 & 5	no	4 & 5	yes
				$m_{3,4}$					
2& 3	no	2& 3	yes	2& 3	no	2& 3	yes	2& 3	no
2& 4	no	2& 4	no	2& 4	no	2& 4	no	2& 4	no
2& 5	no	2& 5	no	2& 5	no	2& 5	yes	2& 5	no
3& 4	no	3& 4	yes	3& 4	no	3& 4	no	3& 4	no
3& 5	no	3& 5	no	3& 5	no	3& 5	no	3& 5	no
4& 5	no	4& 5	no	4& 5	no	4& 5	no	4& 5	no

Table 9. Pattern results of the Scheffé multiple comparison for a cycle and a trend.

Period comparison	Cycle	Trend
1 & 2	yes	yes
1 & 3	no	yes
1 & 4	yes	yes
1 & 5	no	yes
2 & 3	yes	yes
2 & 4	no	yes
2 & 5	yes	yes
3 & 4	yes	yes
3 & 5	no	yes
4 & 5	yes	yes



Site	Latitude (North)	Longitude (West)	Altitude (m)
MONTALEGRE	41.80	−7.78	1069
PORTO-SERRA DO PILAR	41.10	−8.60	100
PENHAS DOURADAS	40.40	−7.55	1388
CHOUTO	39.16	8.21	126
PAVIA	38.90	−8.02	192
LISBOA	38.70	−9.15	114
EVORA	38.60	−7.90	309
BEJA	38.00	−7.87	246
S. B. ALPORTEL	37.20	−7.90	325
FARO	37.00	−7.97	8

Fig. 1. Portugal (location of the stations).

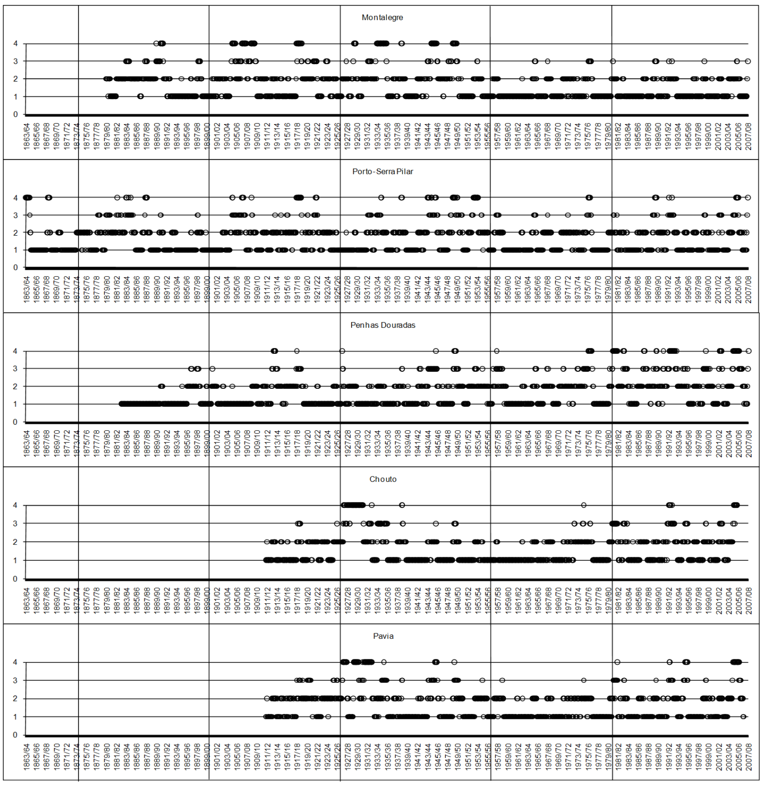


Fig. 2. Drought classes through time by location (sub-periods are indicated with vertical lines).

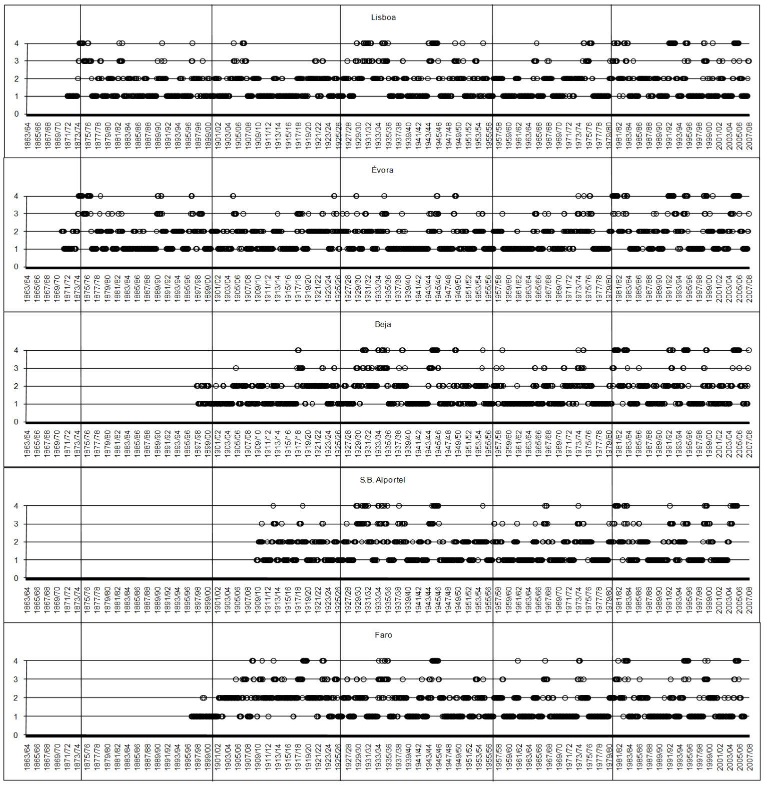


Fig. 3. Drought classes through time by location (cont.) (sub-periods are indicated with vertical lines).