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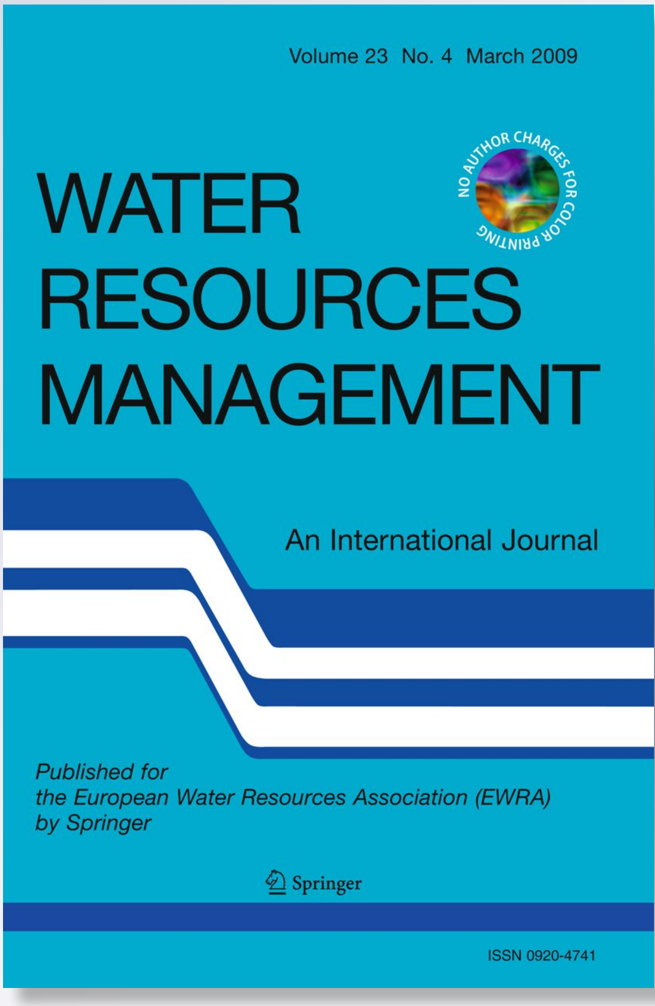

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Regional Frequency Analysis of Droughts in Portugal

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Abstract This study investigated the frequency of droughts for the period September 1910 to October 2004 in mainland Portugal, based on monthly precipitation data from 144 rain gauges distributed across the country. The drought events were characterized using the standardized precipitation index (SPI) applied to time scales of 1, 3, 6 and 12 consecutive months. Based on the SPI time scale series a regional frequency analysis of drought magnitudes was undertaken using two approaches: annual maximum series (AMS) and partial duration series (PDS). Three spatially defined regions (north, central and south) were identified by cluster analysis and analyzed for homogeneity. Maps of drought magnitude were developed using a kriging technique for several return periods. Similar uniform spatial patterns were found throughout the country using the AMS and PDS approaches. For several SPI time scales a comparison of the observed and estimated maximum magnitude (269-year empirical return period) showed that the AMS combined with the selected probability distribution models (Pearson type III, general Pareto and Kappa) provided better results than the PDS approach combined with the same models. A general and simplified characterization of drought duration revealed a relatively uniform pattern of droughts events across the country.

Keywords Standardized precipitation index (SPI) · Annual maximum series · Partial duration series · Regional frequency analysis

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1 Introduction

A significant problem in drought risk analysis is assessment of the rarity of events such as long or severe droughts. This problem is complicated by the lack of a precise definition of drought. Tallaksen and Van Lanen (2004) defined drought as "a sustained and regionally extensive occurrence of below average natural water availability". Drought is generally associated with a continuous period of low precipitation, soil moisture or water availability relative to the normal levels in that locality and to which the affected community is accustomed. Differences in the perception of droughts have led to the adoption of numerous definitions that do not have general acceptance or worldwide applicability, as reviewed by Wilhite and Glantz (1985), and Tate and Gustard (2000).

The definition based on deviation from normal conditions or from reference stages implies that droughts can occur in any hydroclimatological region and at any time of the year with the same probability. To identify, characterize and quantify the attributes of the various components (e.g. climatic, environmental, agricultural, hydrological) of droughts in different regions, various indices have been proposed (e.g. Palmer 1965; Rossi et al. 1992; McKee et al. 1993; Byun and Wilhite 1999; Heim 2002; Hisdal et al. 2004; Tsakiris et al. 2007; Pandey et al. 2008; Nalbantis and Tsakiris 2009). According to Cancelliere and Salas (2004), extreme droughts can be characterized by their duration, severity (magnitude or intensity), spatial extent, and frequency or return period. Extreme droughts are complex phenomena that evolve through time and space in a more or less random fashion, and can be characterized by their beginning, duration, magnitude or intensity, spatial extent and end.

The standardized precipitation index (SPI) is a commonly used drought index originally developed by McKee et al. (1993). It remaps the precipitation records into a standardized probability distribution function, with an index of zero indicating the median precipitation amount; a negative index indicates drought conditions and a positive index indicates wet conditions. The calculation and advantages of the SPI index have been comprehensively described by Edwards and McKee (1997), Guttman (1998, 1999), Hayes et al. (1999), Lloyd-Hughes and Saunders (2002) and Vicente-Serrano (2006a). According to the definition of the SPI, the probability of occurrence of a specific SPI value is the same for the different stations distributed over an area i.e. the index cannot be used for estimating spatial differences in drought risk. Nevertheless, the temporal patterns of drought can differ because of the temporal succession of SPI values. This can be used to analyze spatial differences in drought risk related to drought magnitude and duration (Dracup et al. 1980). An SPI series characterized by frequent but short wet and dry periods indicates a different drought risk than an SPI series with fewer but longer dry periods. The latter indicates a greater drought risk because the magnitude of a drought is proportional to its duration, and a higher magnitude involves a more extreme water deficit (Vicente-Serrano et al. 2004).

Tallaksen (2000) and Tallaksen and Van Lanen (2004) have provided a comprehensive review of drought risk assessment based on frequency analysis for within-year droughts. Two common methods for identifying extreme events from a drought index time series are the block maxima (BM) and the partial duration series (PDS) approaches. For the BM approach a block size of one year (annual maximum series, AMS) is commonly used in hydrological studies. However, based on a case study in Norway, Engeland et al. (2004) found that to avoid model bias using daily stream flow data to establish drought deficit volumes a block size of at least two years was required. They achieved good results with either approach, although the use of the PDS allowed inclusion of a greater number of events in the series, and thus reduced the standard errors in the event estimates. However, there remain many uncertainties in the choice of extreme values used in drought analysis.

The analysis of extremes in dry spell series is based on an AMS adjusted using the Gumbel distribution (Gupta and Duckstein 1975; Ascaso and Casals 1981; Lana and Burgueño 1998). The AMS uses the most extreme dry spell in each year, so the series length equals the number of years for which records are available. However, this approach is not free from problems. Its main drawback is the loss of information about other dry spells in the annual cycle, which may also represent extreme events that ultimately are worse than the maximum dry spells in other years.

We carried out a comprehensive analysis of the magnitude and duration of droughts in Portugal using a high density database (144 rain gauges), and assessed the results in terms of better management of water resources and the mitigation of drought events. The time series of the SPI for the 144 rain gauges were analyzed using the AMS and PDS approaches. The drought magnitude and duration series were obtained as described by Vicente-Serrano et al. (2004). No comprehensive study aimed at providing reliable statistical tools for drought analysis in Portugal has previously been reported.

2 Study Area and Data Processing

Portugal is located in the western part of the Iberian peninsula and encompasses both Atlantic and Mediterranean climatic zones. The mean annual rainfall varies from more than 3000 mm in the northwest to less than 400 mm in the south, and follows a complex spatial pattern (N–S/E–W) that is closely related to the topography. Topography is one of the major factors affecting the distribution of precipitation. As water availability decreases the hydrological regime within and among years becomes more irregular (Portela and Quintela 2006). This makes the characterization of droughts an important issue for water resources management, particularly in the semiarid central and southern regions of Portugal.

Santos et al. (2010) identified the general spatial pattern of droughts in Portugal using the SPI. Based on 144 rain gauges (locations shown in Fig. 1) they identified three well defined subregions (northern, central and southern Portugal) having differing drought patterns (clusters 1, 2 and 3 in Fig. 1, respectively). In the present study the temporal pattern of droughts in each subregion was characterized to enable drought frequency analysis. The number of rain gauges was 56, 53 and 35 for clusters 1, 2 and 3, respectively. Drought data were extracted from the SPI1, SPI3, SPI6 and SPI12 time series (representing data at the scale of 1, 3, 6 and 12 months, respectively).

Several economic activities in Portugal are particularly prone to the effects of drought. These include nonirrigated agriculture (mainly cereals), where short SPI temporal scales indicative of meteorological and agricultural droughts are most relevant. In addition, increased tourism and irrigated agriculture have considerably increased water demand, particularly in the drier southern regions. The water restrictions and loss of irrigated land resulting from hydrological droughts is increasingly detrimental to society and the economy, as noted by Vicente-Serrano (2006b) for all the Iberian peninsula though based on a much sparser rain gauges distribution. Consequently the use of SPI with a longer time scale (12 months) needs to be considered for suitability in the monitoring of hydrological droughts (Hayes et al. 1999; Komuscu 1999). Although the absolute number of dry episodes decreases with increasing time aggregation in the SPI, the episodes tend to be much longer and show a much higher level of persistence, as McKee et al. (1993) highlighted in analysis of time series in Boulder Colorado, USA.

According to McKee et al. (1993), drought comprises a beginning date, an end date, a current drought intensity and a drought magnitude. The duration of a drought event (D_i) is

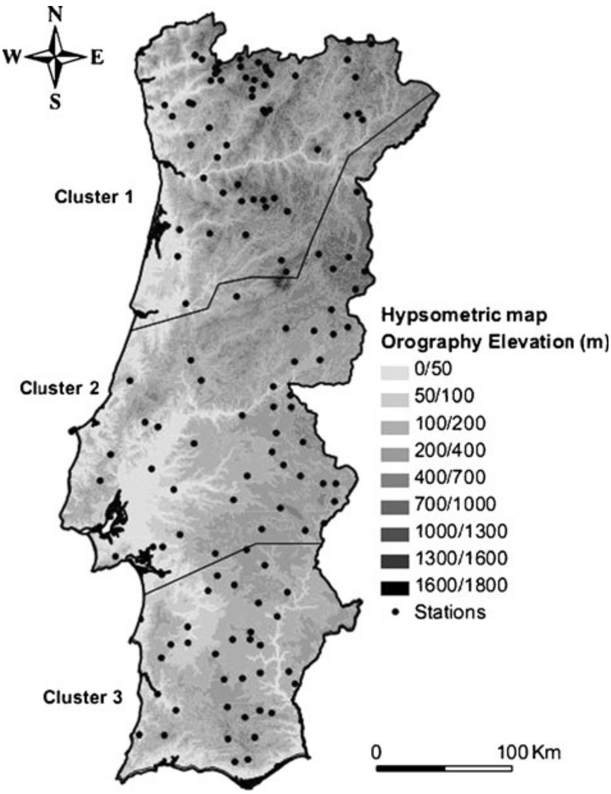


Fig. 1 The three regions with different temporal drought patterns, obtained by cluster analysis (reproduced from Santos et al. 2010)

the period of time from commencement of the drought until its end. Drought intensity can be either the value of the SPI at any moment (D_{int}) or the maximum of SPI value during a drought event (D_{mi}) The drought magnitude (D_m) is equal to the accumulated values of the SPI during each drought event (Fig. 2).

The present study aimed to provide a comprehensive characterization of the magnitude and duration of droughts in Portugal, and to identify statistical tools for future drought studies. This involved analysis of the SPI based on time series data from 144 rain gauges (Fig. 1) using the AMS and PDS approaches.

The AMS is based on the single most severe drought event each year (the greatest magnitude), provided that it exceeds a given threshold. The length of the series thus

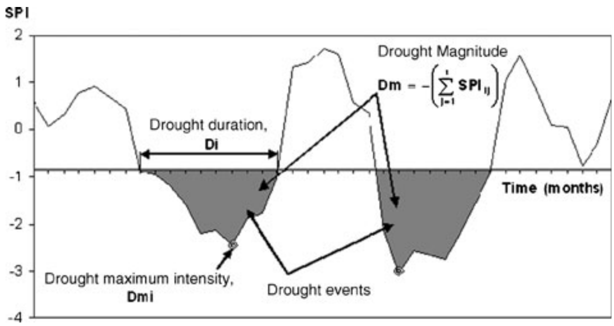


Fig. 2 Definition of drought properties based on the SPI index

obtained is equal to the number of years for which SPI values are available. The years without droughts or with droughts below the threshold are assigned a value of zero (Tallaksen et al. 1997). This is the more common approach because of its simplicity. However, as it considers only one value per year it is more demanding because longer series are required, which could be a disadvantage.

The PDS is based on the magnitude of all drought events above a certain threshold, which results in a much more comprehensive series that has no limit in the number of events included, provided they are all discrete. The average number of droughts per year is equal to the total number of drought events divided by the length of the SPI series.

A threshold of −0.84 was adopted in the PDS and AMS analysis. This is equivalent to the 20th percentile of the normal cumulative distribution (the driest 20% of months in the series are included below this percentile), and represents a moderate drought (Agnew 2000).

The AMS and PDS approaches have been applied previously, although in specific contexts. Tallaksen et al. (1997) used both approaches to study the extremes of drought duration and deficit volume in two Danish catchments with different flow regimes. Vicente-Serrano and Begueria (2003) used a 50-year time series of daily precipitation in the middle Ebro valley (northeastern Spain) to predict the risk of extreme dry periods. They compared the observed and estimated maximum dry periods (50-year return period) using the generalized Pareto (GP) distribution combined with a PDS, and the Gumbel distribution fitted to an AMS. Cunnane (1973) was among the first to compare the PDS and AMS approaches in the statistical analysis of extreme hydrologic events (flood discharges). They were also compared by Madsen et al. (1997a, b). Martins and Stedinger (2001) showed that when fitting three-parameter generalized extreme value models using generalized maximum likelihood estimators, the average gains from using historical flood and paleo-flood information were similar using the AMS or the PDS approaches.

An AMS can include zero values. In this case the drought frequency analysis can be based on the non-zero values combined with a correction factor that accounts for the number of zero values in each series. A similar procedure was applied by Edwards (2001) and Vicente-Serrano (2006a). However, it has been reported that too many zero-rated drought years reduces the sample size and seriously affects extreme value modeling (Stedinger et al. 1993; Tallaksen et al. 1997), but this issue was not addressed in the present study.

The PDS approach (also referred to as the peak over threshold method, as it was initially applied to flood analysis) was introduced by Shane and Lynn (1964) and Todorovic and Zelenhasic (1970). In the PDS model applied to the present study all drought events were taken into account, and intuitively this should provide a more complete reflection of the historic sequence of drought events than the AMS approach.

Depending on the time scale of the SPI, two problems can arise in use of the PDS approach: (i) a large number of minor droughts can distort the extreme event modeling, creating dependency structures; and (ii) for long SPI time scales the drought magnitude series may be too short to enable reliable estimates. In the analyses applied to the data no dependent drought events were detected.

3 Methodology

3.1 Return Period

The return period is a useful statistic for characterizing extreme hydrologic events, such as droughts. Its assignment to severe droughts can provide useful information about improvements in water systems management under dry conditions (Bonaccorso et al. 2003). The return period of an event (T) can be defined in several ways depending on the application and user. Some (e.g. Lloyd 1970; Loaiciga and Mariño 1991; Shiau and Shen 2001) have defined the return period as the average elapsed time between the occurrences of critical events (floods or droughts). An alternative definition is the average number of trials (usually years) to the first occurrence of an event of magnitude greater than a predefined critical event (Benjamin and Cornell 1970). Bonaccorso et al. (2003) developed a return period concept that extends the method proposed by Shiau and Shen (2001), as it expresses the return period of drought severity as a function of the statistical characteristics of historical long records of precipitation, and of a threshold parameter.

In the present study the original concept of the return period (Haan 1977) was used, i.e. the average number of years between events above a threshold magnitude. According to Beguería (2005) this definition of T has the following underlying assumptions (which are valid for both the AMS and PDS approaches):

(1) The extremes of the variable under consideration are random, and thus can be described by a probability distribution function.
(2) This distribution function does not change from sample to sample (homogeneity assumption).
(3) The data are independent.

Some probability distribution functions are not defined for zero (x=0). If such distributions are applied to series of the annual maxima of drought duration, intensity or magnitude (which may include zero values representing periods without droughts, or with droughts below a given threshold), a corrected non-exceedance probability (F′) is used, according to the following expression:

$$F' = q + (1 - q)F \tag{1}$$

where q is the probability of zero values, and can be calculated as the ratio of the number of time intervals without drought occurrences (m) to the total number of time intervals in the recording period, n (q = m/n) (Vicente-Serrano 2006a).

In contrast to the AMS approach, where the sampling time interval for the observations is known (one year), the PDS approach assumes that the frequency of events in a given time period is random, considering the time between events and the number of events (Beguería 2005).

One of the simplest and most widely used models assumes a Poisson process for event arrivals (Cunnane 1979; Beguería 2005). Under the Poisson assumptions the return period (years) for the probability of non-exceedance of F is calculated as:

$$T = \frac{1}{\lambda\,(1 - F)} \tag{2}$$

where λ is the average number of occurrences per year. Todorovic and Zelenhasic (1970), Ashkar and Rousselle (1987) and Rosbjerg et al. (1992) provide examples of the application of the previous return period formulation The plotting position formula of Hosking (1990) was used to evaluate any empirical non-exceedance probability.

3.2 Regional Frequency Analysis

The regional frequency analysis was applied separately to each of the three cluster regions in Fig. 1. In general terms these regions reflect the major factors interacting to influence the spatial and temporal distribution of precipitation in Portugal: proximity to the Atlantic Ocean, orography and latitude. Santos et al. (2002) observed differences in the distribution of correlations between the frequency of wet circulation weather types and rainfall amounts, and suggested that the precipitation regime in northern Portugal is dominated by orographic factors, while in southern Portugal the dominant factor is cyclogenetic activity (Trigo and Camara 2000). Corte-Real et al. (1998) showed that in Portugal four weather circulation patterns or weather regimes are important in precipitation variability and its relationship to the variability of large-scale atmospheric circulation.

Northwest Portugal has one of the highest mean annual rainfalls in Europe (approximately 3000 mm), predominantly because of the influence of the Atlantic Ocean. The central region of Portugal is climatically distinct from the north because it is characterized by the loss of moisture from air masses coming from the Atlantic as they descend from high altitudes (Ribeiro 1998). The transition between the north and central regions is effectively an orographic barrier (the Cordilheira Central) that results in the northern interior being drier than the coast. Relative to the humid north, the southern region is very dry (mean annual rainfall <500 mm) with high intra and inter annual variability, and is more prone to water scarcity. The separation between the central and southern regions is not clear, as the rainfall pattern of the Tagus River basin region is poorly characterized because of the small number of rain gauges located there. As noted above the number of rain gauges in each of cluster regions 1, 2 and 3 was 56, 53 and 35, respectively (144 in total).

The regional frequency analysis followed the methodology of Hosking and Wallis (1997), and involved the three main steps:

(i) screening of the data and testing of regional homogeneity;
(ii) identification of the regional probability distribution function; and
(iii) development of regional frequency relationships for gauged and non-gauged sites.

The above procedures have been described in detail by Hosking and Wallis (1997), and Naghettini and Pinto (2007), and are summarized below.

3.3 Data Screening and Testing for Regional Homogeneity

In assuming the homogeneity of a region the first step is to evaluate the consistency of the available data. In this study the tests described by Hosking and Wallis (1997) were used to assess the discordance and heterogeneity of each of the three subregions considered in the drought analysis (Fig. 1). To identify sites that were grossly discordant within a group of sites, Hosking and Wallis (1993, 1995) developed a statistic (the discordancy measure; S_i) based on L-moments. The statistic considers the L-moment ratio (L-coefficient of variation or L-CV, L-skewness and L-kurtosis) of each site to describe the site in a three-dimensional space. The discordancy measure for station l is given by:

$$S_l = \frac{N_s}{3\,(N_s - 1)}\ (u_l - \overline{u})^{T_m}\ S_{cm}^{-1}(u_l - \overline{u}) \tag{3}$$

where N_s is the number of measurement stations in the region; S_{cm} is the sample covariance matrix; u_l is the vector containing the L-coefficient of variation (t), L-skewness (t_3) and L-kurtosis (t_4); $\overline{u}$ is a vector (3×1) representing the arithmetic average of u_l for the N_s stations; and T_m represents the transposed matrix and −1, the inverse matrix.

Hosking and Wallis (1993) suggested a maximum limit of $S_I=3$ for a station to be considered part of a region, and noted that this measure is only useful for regions with $N_s \geq 7$. The number of rain gauges in each region in the present study exceeded this limit.

The heterogeneity measure of Hosking and Wallis (1993) involved comparison of the sample variability of the L-moment ratios with the variation that would be expected in a homogeneous region. The latter is estimated by repeated simulations of homogeneous regions with samples drawn from a four-parameter Kappa distribution (see Hosking and Wallis 1997; pp. 202–204). This statistic aims to estimate the degree of heterogeneity in a group of sites, and to assess whether they represent a homogeneous region. Santos et al. (2010) used two equivalent, but conceptually different, techniques only to group stations and to identify regions that were never tested, to evaluate their statistical homogeneity (as recommended by Hosking and Wallis 1997). This was the base point for the regional analysis using graphical and analytical measures of homogeneity.

To establish what would be expected in a homogeneous region, 500 data sets were generated based on the regional averaged L-moment ratios taken from the original sample using the four-parameter Kappa distribution. For each dataset or region a statistic (V_k) was calculated, and based on the vector of the V_k values the mean (μ_{vk}) and the standard deviation (σ_{vk}) were calculated.

The heterogeneity measure (H_k) was the computed according to the equation of Hosking and Wallis (1997):

$$H_k = \frac{V_k - \mu_{vk}}{\sigma_{vk}} \tag{4}$$

where is the test statistic, with the variable k assuming values of 1, 2 or 3 in referring to the L-coefficient of variation (t), L-skewness (t_3) or L-kurtosis (t_4), respectively.

For $k=1$ the test statistic V_1 is given by:

$$V_1 = \left[\frac{\sum_{j=1}^{N_s} N_j \left(t^j - t^R\right)^2}{\sum_{j=1}^{N_s} N_j}\right]^{\frac{1}{2}} \tag{5}$$

where N_s is the number of stations, N_j is the record length at station j, t^j is the L-coefficient of variation for station j, and t^R is the regional averaged L-coefficient of variation.

The V_1 statistic measures heterogeneity only in relation to dispersion of the samples, as it is based solely on the differences between the sample L-CVs in the region. As such, it is insensitive to heterogeneity that arises between sites having equal L-CVs but different L-skewness. To overcome this limitation, Hosking and Wallis (1993) included two additional heterogeneity measures, H_2 and H_3, but these were not used in this study.

In relation to limits for the heterogeneity measures, Hosking and Wallis (1997) suggested that a group of sites be considered "acceptably homogeneous" if $H_1 < 1$, "possibly heterogeneous" if $1 \leq H_1 < 2$, and "definitely heterogeneous" if $H_1 \geq 2$. The measures H_2 and H_3 have similar numerical limits for acceptable homogeneity. Hosking and Wallis (1997) judged H_2 and H_3 to be poorly measures than H_1, and noted that it rarely yields values greater than 2, even for grossly heterogeneous regions. Viglione et al. (2007) showed that H_2, which is based on L-skewness (t_3), lacks power as a heterogeneity measure. Therefore, H_1 is the most important heterogeneity measure to be accounted for, and was therefore included in this study.

3.4 Identification of Regional Distribution Models: L-Moment Ratio Diagrams and the Goodness-of-fit Z Statistic

Once the homogeneity of a given region is confirmed it is necessary to identify an underlying probability model for the variable under consideration, in this case the drought magnitudes based on SPI values at various time scales (and less than the threshold of −0.84; Fig. 3). To achieve this, various probability distribution models were applied to the absolute values of the drought magnitudes.

One of the procedures for identifying the regional probability distribution function assumes that the sites from a homogeneous region follow the same distribution function, apart from a site-specific scaling factor represented by the mean of the site-specific data (Dalrymple 1960; Hosking and Wallis 1997; Naghettini and Pinto 2007).

The L-moment method provides estimates for a p-parameter probability distribution function by matching the first p sample L-moments of each station to the corresponding distribution parameters. Five three-parameter distributions, the generalized logistic (GL), generalized extreme value (GEV), generalized Pareto (GP), log normal (LN) and Pearson type III (PEIII) distribution were used to assess each region, following the procedures proposed by Hosking and Wallis (1997). The parameters of those distributions are effectively obtained using the first four sample L-moments.

Various goodness-of-fit techniques were available to identify the best probability distribution function for each region. However, based on the procedures of Hosking and Wallis (1997) and because the best fit to the observed regional data should indicate the most appropriate distribution (Chen et al. 2006), L-moment ratio diagrams and a goodness of fit measure (the Z statistic) were used.

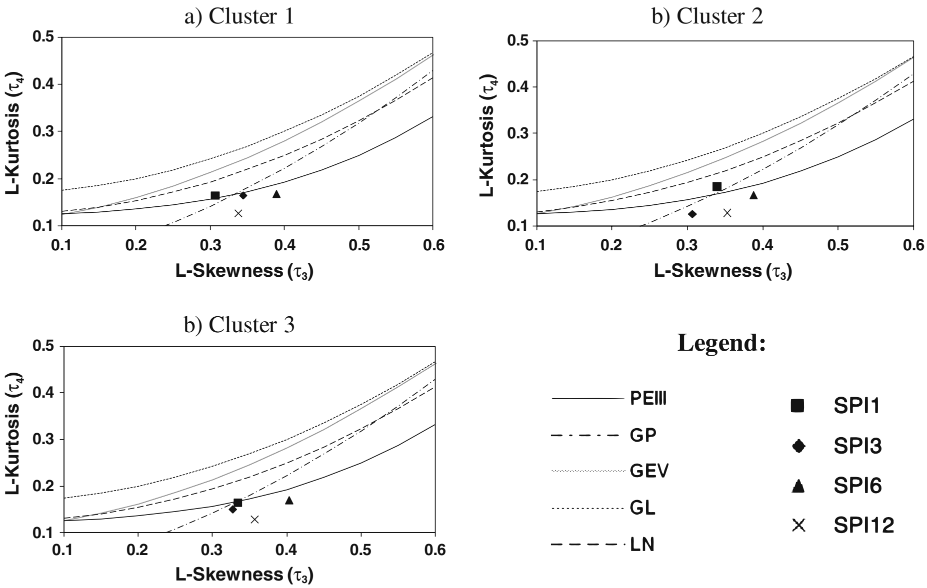


Fig. 3 The AMS approach to identification of subregional probability distribution functions using L-moment ratio diagrams: **a** cluster 1; **b** cluster 2; **c** cluster 3. GEV: generalized extreme value; GL: generalized logistic; PEIII: Pearson type III; LN: lognormal-3; GP: general Pareto

The L-moment ratio diagram is a graph where the sample L-moment ratios, L-skewness and L-kurtosis are plotted as a scatterplot and compared with the theoretical L-moment ratio curves of the candidate distributions. L-moment ratio diagrams have been suggested to be a useful tool for discriminating among candidate distributions for describing regional data (Hosking 1990; Stedinger et al. 1993; Hosking and Wallis 1997), and have been extensively used as part of the probability distribution function selection process for regional data (Schaefer 1990; Pearson 1993; Vogel and Fennessey 1993; Vogel et al. 1993a, b; Vogel and Wilson 1996; Norbiato et al. 2007; Vicente-Serrano 2006a).

Two representations used to assist in the selection of statistical distributions are the sample average and the line of best fit, which can be plotted on the same graph to facilitate selection of the best fit distribution. From several simulations Peel et al. (2001) concluded that for homogeneous data it is best to base the distribution selection on the sample average than the line of best fit through the data points. In the present study only the sample average criterion was followed.

The Z statistic was developed for three-parameter distributions, and quantifies how well the theoretical L-kurtosis of the fitted distribution matches the regional average L-kurtosis of the observed data. The Z statistic was developed by Hosking and Wallis (1993), and is commonly used for selection of regional probability distributions. The Z statistic for a given distribution (Hosking and Wallis 1997) is expressed as:

$$Z = \frac{\left(\bar{t}_4^R - t_4^{dist}\right)}{\sigma_{t_4}} \tag{6}$$

where $\bar{t}_4^R$ is the regional average L-kurtosis, σ_{t_4} is the standard deviation of $\bar{t}_4^R$, and t_4^{dist} is the L-kurtosis of a fitted distribution. The probability distribution function with the smallest value of |Z| is considered to be the best choice among the possible statistical distributions. At a significance level of α=10%, the critical value of Z is 1.64. Accordingly, for a particular probability distribution, if $|Z| \leq 1.64$ the distribution is considered acceptable for representing the sample data at α=10% (bilateral test).

Where none of the three-parameter distributions tested fulfill the criteria of $|Z| \leq 1.64$, a more robust probabilistic model should instead be considered. In these circumstances Hosking and Wallis (1997) recommended the use of the four-parameter Kappa distribution, which is more flexible; this approach was adopted in the analyses in this study.

Hosking and Wallis (1997) also noted that the Z statistic is particularly inconsistent when data show strong serial and/or cross correlation, because both tend to increase the variability of $\bar{t}_4^R$. In this case the value of σ_{t_4} becomes too small and the Z statistic too large, giving a false sense of no adjustment.

4 Data Analysis and Results

4.1 Regional Homogeneity Tests and Regional Frequency Distributions

Based on 94 years of monthly precipitation data at the 144 rain gauges (Fig. 1), series of the SPI at 1, 3, 6 and 12 month time scales were obtained (Santos et al. 2010). In addition, the corresponding magnitude and duration series for SPI values ≤ –0.84 were obtained following the procedure of Vicente-Serrano et al. (2004). The precipitation records were obtained from the database of the Portuguese Water Institute (INAG). The AMS and PDS approaches were then applied to the SPI series for each region. For the AMS approach this resulted in a drought magnitude series with 94 values (i.e. equal to the number of years of rainfall records) when the zero values were included, and a variable number of events for the different SPI time scales and subregions when zero values were excluded. The average lengths in the PDS approach were also variable (Table 1). Because of the statistical nature of the SPI, for all subregions the number of drought magnitude events decreased as the SPI time scale increased (Table 1).

The discordancy measure was then applied to each subregion to identify those stations with sample statistics markedly different from the majority of the stations belonging to that region. The test based on the discordancy measure was repeated for the three subregions in Fig. 1, and for the four SPI time scales. In the AMS approach the data were checked to verify the validity of records. As a consequence, three stations in cluster 1, seven stations in cluster 2 and three stations in cluster 3 were found to have clearly discrepant data, and were removed. The discrepant stations removed from the PDS series included five from cluster 1, two from cluster 2 and four from cluster 3. Thus, the study was based on data from 131 and 133 rain gauges for the AMS and PDS approaches, respectively.

The heterogeneity measures are shown in Table 2, and indicate that with the AMS approach H_1 only exceeded the threshold in cluster 1 for durations of 1 month (SPI1), and with the PDS approach H_1 only exceeded the threshold in cluster 1 at the 1- and 6-month time scales (SPI1 and SPI6). Negative values were also found at all time scales, for the 12-month time scale (SPI12) in all subregions, and particularly for cluster 3 with both the AMS and PDS approaches. According to Hosking and Wallis (1997), negative values indicate that there is less dispersion among the at-site statistics than would be expected in a homogenous region with independent at-site frequency distributions. This also suggests extensive cross-correlation among the frequency distributions of the sites. This may be reasonable for longer SPI time scales, as the low frequency of the events is associated with longer durations, which increases the possibility of almost simultaneous occurrences at several stations because of their geographical proximity. According to Davis and Naghettini (2001), all H_1 values below –2.0 make the analysis more accurate, and the data should be reexamined. Only for SPI12 in cluster 3 and the PDS approach did such values occur, and research is ongoing to quantify their effect.

The L-moment ratio diagrams are shown in Figs. 4 and 5 for the AMS and PDS approaches, respectively. The averages of L-skewness and L-kurtosis for the three subregions are plotted together with the L-skewness/L-kurtosis relationships for various distributions.

For the AMS approach (Fig. 4) the best choices for cluster 1 were the PEIII distribution for time scales of 1, 3 and 6 months, and the GP distribution for 12 months. For cluster 2

Table 1 Average lengths of the magnitude series for the AMS (without zeros) and PDS approaches for the four SPI time scales and the 3 subregions (CL1, CL2 and CL3)

Events	PDS			AMS		
	CL1	CL2	CL3	CL1	CL2	CL3
SPI1	149	124	118	83	77	77
SPI3	102	106	109	75	77	76
SPI6	68	74	77	59	61	61
SPI12	39	42	44	43	44	44

Table 2 Heterogeneity (H_1)values for the three AMS and PDS subregions (clusters) and the four SPI time scales

Time Scale	Cluster 1 AMS–H_1	Cluster 2	Cluster 3	Cluster 1 PDS–H_1	Cluster 2	Cluster 3
SPI1	**2.85**	−1.52	−0.24	**3.42**	0.67	−0.75
SPI3	0.46	0.07	−0.46	1.20	0.78	−1.29
SPI6	−0.14	−1.91	−1.13	**2.77**	−1.89	−0.88
SPI12	−1.83	−1.56	−1.90	−0.40	−1.58	−3.19

Values exceeding the heterogeneity threshold (H_1=2) are marked in bold

the PEIII distribution best described SPI6 and SPI12, while the GP distribution best described SPI1 and SPI3. The results for cluster 3 were similar to those for cluster 2.

The diagrams for the PDS approach (Fig. 5) show a wider distribution of average points, possibly confirming that in this approach the drought magnitude time series is more variable among the SPI time scales than in the AMS approach. In all subregions there was a close match between the SPI1 and the GP distribution, while the PEIII distribution was the better model for the other time scales because the corresponding average points were closer to the theoretical line for the distribution.

In general terms the L-moment diagrams did not provided clear information about the fitting of models using either approach, or for the three subregions. The average points were always located near the GP or the PEIII distributions, indicating that either provides a good fit to the data, depending on the SPI time scale. To resolve this uncertainty we used the

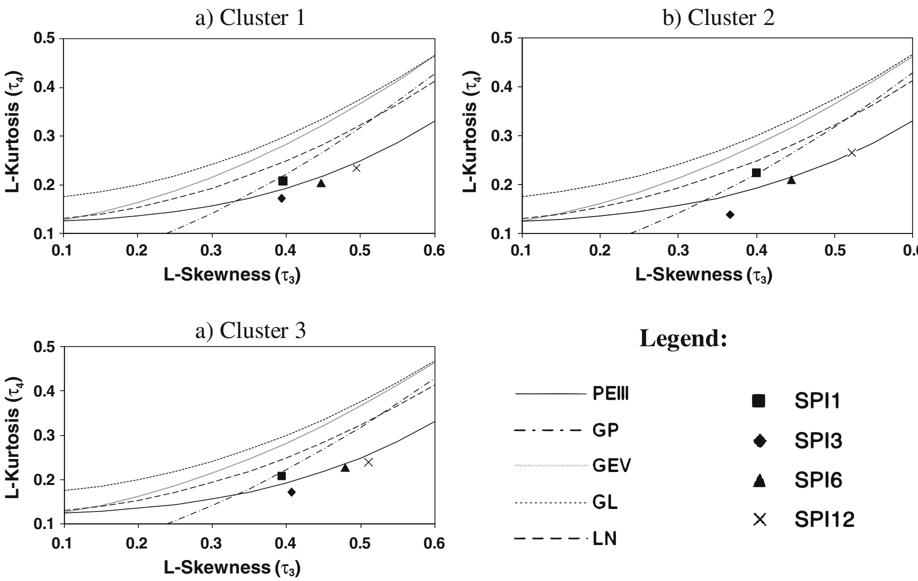


Fig. 4 The PDS approach to identification of subregional probability distribution functions using L-moment ratio diagrams: **a** cluster 1; **b** cluster 2; **c** cluster 3. GEV: generalized extreme value; GL: generalized logistic; PEIII: Pearson type III; LN: lognormal-3; GP: general Pareto

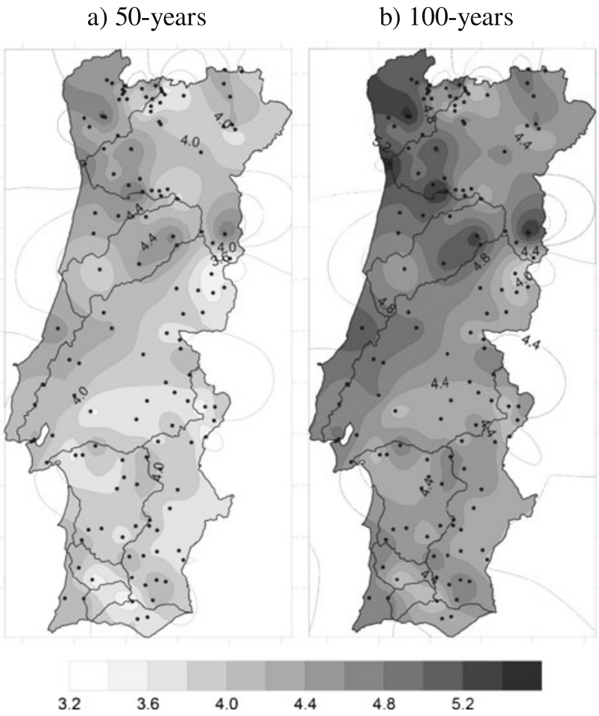


Fig. 5 AMS approach applied to SPI1. Maps of drought magnitude for the return periods: a) 50 years and b) 100 years (the dots represent the rain gauges)

quantitative Z statistic (Eq. 6), which indicates how well the theoretical L-kurtosis of the fitted distribution matches the regional average L-kurtosis of the observed data.

The values of the Z statistic for the best fit of the PEIII and GP probability distribution functions are presented in Table 3 (AMS approach) and 4 (PDS approach).These Z values are consistent with the L-moment diagrams in Figs. 4 and 5, and indicate a shift from the GP distribution to the PEIII distribution. This was particularly the case for the PDS approach when moving from the SPI1 to SPI6 and SPI12. With the AMS approach, for cluster 1 the PEIII distribution provided the best fit for half of the time scales. For cluster 2 there was a better fit of the GP distribution for the two shortest time scales, and the PEIII distribution for the two longer time scales. For cluster 3 only the SPI3 could be modeled by the GP distribution, while the PEIII distribution provided the best fit for the other SPIs. In some cases, for both the PDS and AMS approaches the quality of the fit decreased as the

Table 3 Values of the Z statistic for the three AMS subregions (clusters) and the four SPI time scales

|Z|	Cluster 1		Cluster 2		Cluster 3	
	PEIII	GP	PEIII	GP	PEIII	GP
SPI1	**0.91**	2.58	1.86	1.70	**0.32**	0.33
SPI3	**0.58**	1.24	5.44	3.51	1.03	**0.84**
SPI6	2.26	5.01	2.62	5.15	2.11	5.03
SPI12	4.78	4.94	6.01	6.95	4.29	5.30

The values in bold indicate the best distributions for a significance level of 10%

Table 4 Values of the Z statistic for the three PDS subregions (clusters) and the four SPI time scales

|Z|	Cluster 1		Cluster 2		Cluster 3	
	PEIII	GP	PEIII	GP	PEIII	GP
SPI1	2.96	**1.14**	4.24	**0.49**	2.29	**0.64**
SPI3	2.95	7.15	7.08	9.64	3.13	7.28
SPI6	**1.39**	6.93	**0.33**	5.55	**0.69**	6.11
SPI12	**0.87**	5.95	**0.60**	4.91	**1.05**	5.81

The values in bold indicate the best distributions for a significance level of 10%

SPI time scale increased, with Z values increasing in all subregions. This may be related to the progressively smaller number of events at the longer SPI time scales weakening the fit.

Wherever Z was >1.64 the four-parameter Kappa distribution was adopted, as recommended by Hosking and Wallis (1997). This distribution is a flexible and manageable tool for modeling the empirical and theoretical distributions (Wallis et al. 2007), and therefore can mimic the distributions previously selected. For the AMS approach this occurred for SPI6 and SPI12 in cluster 1; SPI3, SPI6 and SPI12 in cluster 2; and SPI6 and SPI12 in cluster 3. For the PDS approach only SPI3 was modeled by the Kappa distribution (Table 4). Table 5 summarizes the statistical distribution applied to each approach, cluster region and SPI time scale.

To compare the drought magnitudes provided by the AMS and PDS approaches the root mean squared error (RMSE) measure was applied (Willmott 1982). The procedure adopted is similar to that used by Vicente-Serrano and Begueria (2003). For the rain gauges in each region the RMSE measure was applied to the differences between the maximum observed magnitudes and the magnitudes estimated by the chosen regional distribution model, for a

Table 5 Selected statistical distributions for each approach, cluster region and SPI time scale

	AMS			PDS		
	PEIII	GP	Kappa	PEIII	GP	Kappa
Cluster 1						
SPI1	x				x	
SPI3	x					x
SPI6			x	x		
SPI12			x	x		
Cluster 2						
SPI1			x		x	
SPI3			x			x
SPI6			x	x		
SPI12			x	x		
Cluster 3						
SPI1	x				x	
SPI3		x				x
SPI6			x	x		
SPI12			x	x		

particular return period (T). It was assumed that the maximum magnitude value for each rain gauge had an empirical non-exceedance probability (F), given by the Hosking's plotting position formula (the same probability model used to establish the SPI time series). For the AMS approach the resulting return period attended to the correction expressed by Eq. 1, while for the PDS approach Eq. 2 was applied. This resulted in both approaches having an empirical return period of T=269 years.

The lowest value of the RMSE indicated the best approach and regional distribution model. The results (Table 6) clearly indicate that the AMS approach provided the optimum performance, with better results for all the SPI time scales.

Both the AMS and PDS approaches were tested for their ability to perform the regional frequency analysis of the drought magnitude. Based on the heterogeneity measure (Table 2) the AMS approach produced the best results in all clusters. The RMSE between the observed and estimated magnitudes (Table 6) was also highly indicative of the better performance of the AMS approach combined with the PEIII, GP and Kappa distributions. Taking into account the aspects described above, further regional frequency analysis was based only on the AMS approach and the corresponding statistical distributions shown in Table 4.

4.2 Drought Frequency Analysis

Drought frequency analysis, which is focused on the magnitude of droughts, is commonly undertaken using either the AMS or PDS approach. For the spatial characterization of drought events kriging is considered the most accurate method for spatial interpolation (e.g. Akhtari et al. 2009), and is recommended for classification and operational hydrological monitoring systems.

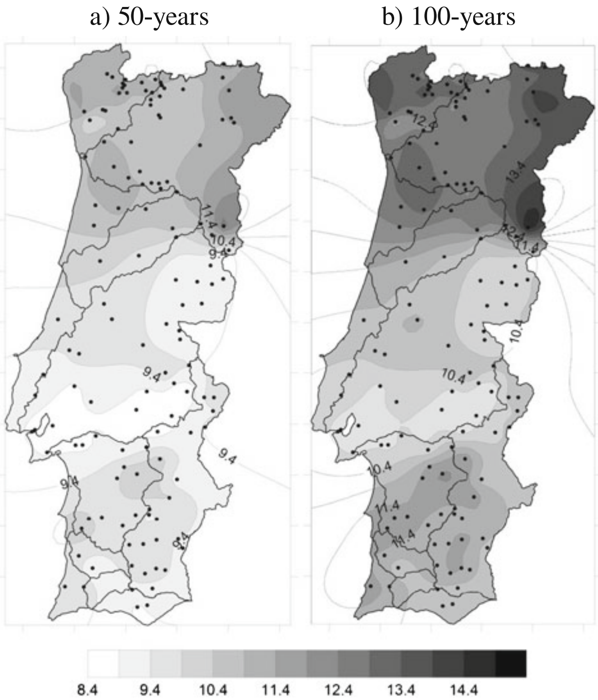
In the present study, maps of drought magnitude based on the AMS approach were created using kriging techniques and the statistical distributions selected for each subregion (Figs. 5, 6, 7, and 8, which include the limits of the main Portuguese watersheds). A default linear variogram with point kriging and the ordinary algorithm (no drift) was used, as described by Isaaks and Srivastava (1989). The return periods adopted for all SPI time scale mapping were 50 and 100 years.

The results (Figs. 5, 6, 7, and 8) showed generally uniform spatial patterns, especially for SPI6 (Fig. 7) and SPI12 (Fig. 8). For SPI1 (Fig. 5) and SPI3 (Fig. 6) the patterns were clearly more heterogeneous over the country for either return period.

Table 6 Comparison of the AMS and PDS approaches. RMSE values for the observed and estimated 269-year return period magnitudes

	Cluster 1 RMSE	Cluster 2 RMSE	Cluster 3 RMSE
AMS			
SPI1	1.29	1.11	0.97
SPI3	3.39	2.74	2.60
SPI6	5.20	3.82	4.92
SPI12	5.44	4.38	5.63
PDS			
SPI1	1.74	1.54	1.40
SPI3	7.48	3.88	2.72
SPI6	9.81	13.23	7.82
SPI12	34.72	31.32	14.19

Fig. 6 AMS approach applied to SPI3. Maps of drought magnitude for the return periods: a) 50 years and b) 100 years (the dots represent the rain gauges)



For the SPI1 time scale the drought magnitude for the northern coastal areas was slightly higher than the continental interior, with maximum values of approximately 4.6 and 5.6, respectively, for the 50- and 100-year return periods.

For SPI3 (and particularly with respect to the 100-year return period) a distinctive pattern was obtained for the central region (cluster 2), with magnitudes smaller than those occurring in the southern and northern regions. The northeastern area (Trás-os-Montes) had the most severe droughts (greatest magnitudes 13.4–15.4). This reflects longer periods with no humid cold air masses coming from the Atlantic Ocean, or the consequences of strong seasonal oscillation between periods dominated by North Atlantic cyclones, which bring rainfall, and periods under the influence of South Atlantic high pressure systems, which are associated with subsident stable air and drought.

In the northeastern area (Fig. 7), higher magnitude values were found for the SPI6. As this is considered to be an agricultural drought index (Hayes et al. 1999; Yamoah et al. 2000), the findings indicate that this region may be at risk because within it agricultural is the main activity. The SPI12 showed a uniform homogeneous distribution (Fig. 8) of drought magnitude values for both the 50- and 100-year return periods. This may be because the aggregated nature of the SPI12 (12 summed month deviations) overcame spatial drought magnitude differences.

The SPI1, SPI3 and SPI6 showed higher average drought magnitudes for cluster 1 (northern region) than for clusters 2 and 3 for the same return periods (Figs. 5, 6, 7, and 8).

Major objectives of the present study were to derive new information on the duration of drought events in Portugal, and to characterize historical temporal patterns. Consequently, we undertook a quantitative analysis of drought duration in the study cluster regions using the AMS magnitude series for all SPI time scales. Using the Thiessen polygon method the weighting of each of the stations in each subregion was computed. For each SPI time scale

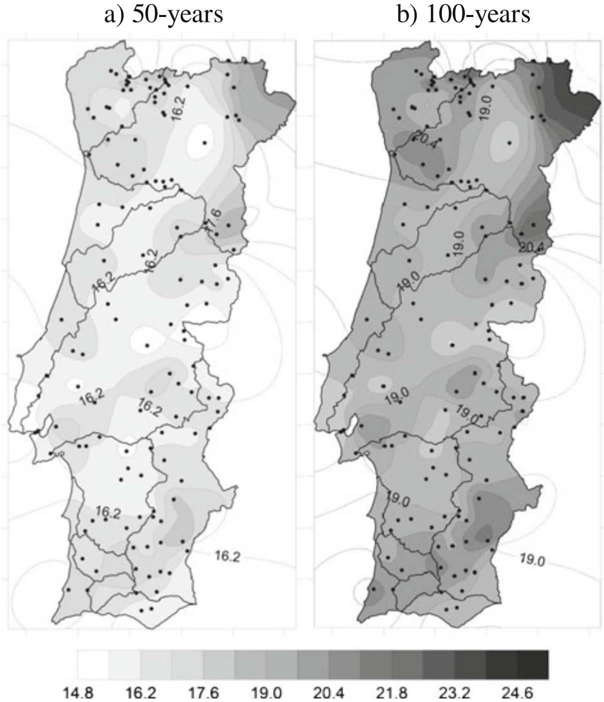


Fig. 7 AMS approach applied to SPI6. Maps of drought magnitude for the return periods: a) 50 years and b) 100 years; (the dots represent the rain gauges)

the weighted number of droughts with a given duration was estimated. The results for durations of 1, 2, 3, 4 and >4 months are shown in Fig. 9.

In the northern region (cluster 1) a slightly higher number of meteorological droughts (SPI1) was detected (weighted number 83 droughts/station in cluster 1, 78 droughts/station in clusters 2 and 3). For SPI3, SPI6 and SPI12 the results were quite similar, showing a uniform distribution of events among the clusters. As previously noted, in any subregion as the SPI time scale increased the number of drought events decreased, because the droughts at longer time scales tend to be longer. Thus, the number of droughts of longer duration increased with longer SPI time scales. The results showed that this pattern was very similar among the three regions. For example in the central region (cluster 2) the weighted number of droughts with a duration of >4 months increased from 0.06 for SPI1 to 18.57 for SPI12, while in the southern region (cluster 3) the respective increase was from 0.02 to 18.00.

5 Discussion and Conclusions

A drought risk assessment for Portugal was undertaken, based on frequency analysis of the annual maximum (AMS) and partial duration (PDS) drought magnitude series for the SPI index at various time scales.

Mapping of the drought magnitudes for two return periods obtained using the AMS and PDS approaches revealed uniform spatial patterns throughout the country. For equivalent time scales the patterns were similar between the two approaches, suggesting no increase in the information obtained using the PDS approach. This is understandable, as the PDS approach did not result in sample sizes much larger than those of the AMS approach, and some of the partial duration samples had even smaller dimension than those of the

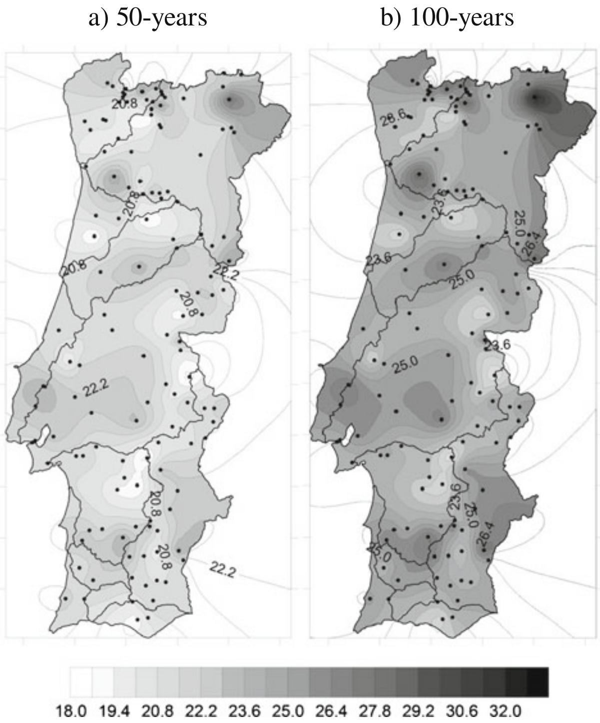


Fig. 8 AMS approach applied to SPI12. Maps of drought magnitude for the return periods: a) 50 years and b) 100 years (the dots represent the rain gauges)

corresponding annual maximum series (e.g. SPI12). Several studies have indicated that the PDS approach is generally more efficient than the AMS approach (e.g. Madsen et al. 1997b; Vicente-Serrano and Begueria 2003; Rosbjerg and Madsen 2004), and have reported that the PDS associated with specific distributions is more effective than the AMS for regionalization of hydrologic variables. However, these findings are in contrast with the results of the present study. Madsen et al. (1997a) also obtained better performance using the AMS approach combined with the generalized extreme values distribution with positive shape parameters, calculated by the probability weighted moments estimation method (PWM), when they applied it to streamflows samples. This paralleled our study for all the regional parent distributions applied.

The results obtained will be markedly influenced by the threshold adopted (SPI < −0.84, which defines the beginning of a drought; Agnew 2000). The threshold is a determining factor in the performance of the PDS approach. Vicente-Serrano and Begueria (2003) found that the last quantile estimates vary significantly with small changes in the threshold. In this study, it is not clear what advantages there are in using the PDS approach for modeling the spatial distribution of drought characteristics (such as magnitude), and so the testing of different thresholds must be followed in a near future.

Several factors account for the spatial patterns in the magnitude of droughts in Portugal, particularly those influencing the spatial variability of precipitation, such as the synoptic weather types and atmospheric circulation patterns (Estrela et al. 2000; González-Hidalgo et al. 2003). A major forcing factor for precipitation in Portugal, and therefore an important indicator of drought magnitude and duration, is the North Atlantic Oscillation (NAO; Zorita et al. 1992; Ulbrich et al. 1999; Goodess and Jones 2002). The NAO is recognized as one of the major factors impacting the hydrological cycle in Portugal (Trigo et al. 2004),

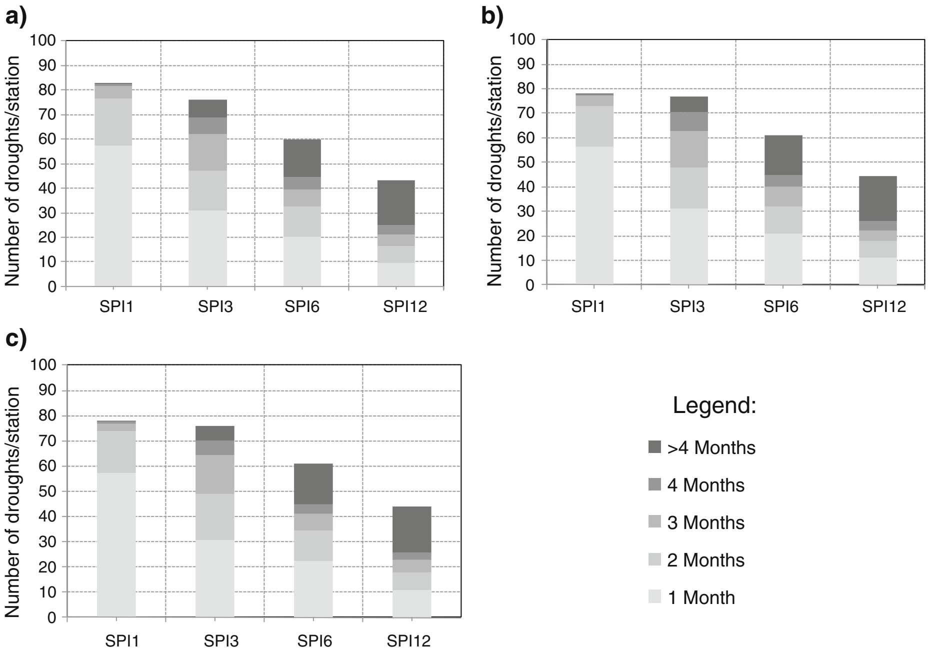


Fig. 9 Period from 1910/11 to 2003/04. Weighted number (per station) of drought occurrences with durations of 1, 2, 3, 4 and >4 months for SPI1, 3, 6 and 12. Results for: **a** the northern region, cluster 1; **b** the central region, cluster 2; and **c**) the southern region, cluster 3

showing a clear spatial gradient from the South (stronger influence) to the North (weaker). In addition, there are also other atmospheric circulation patterns, like the East Atlantic Pattern, that are also affecting precipitation in Portugal (Rodriguez-Puebla et al. 1998). The spatial variability in the influence of atmospheric circulation over Portugal could explain the large existing differences in the drought patterns found in this study.

Additional research is necessary in relation to the heterogeneity measure H_1, particularly with respect to negative values. However, we obtained better homogeneity conditions for regions analyzed using the AMS. The better results obtained using the AMS approach may be because of the longer SPI time scales; using the PDS approach the drought magnitude series may be too short for reliable estimates to be made.

The L-moment diagrams suggested that both the PEIII and GP models provided a good fit to the magnitude series extracted from several of the SPI time scales. Nevertheless, the Z statistic showed that despite the generally good visual adjustment for both these distributions, the Kappa distribution model should be used for the longer SPI time scales, as higher Z statistic values (> 1.64) were obtained in these cases. This distribution was also used successfully for drought risk assessment by Werick et al. (1994) for the US National Drought Atlas. Based on the RMSE error measure, better quantile estimates were obtained using the AMS approach in comparisons of the observed maximum magnitudes with the magnitudes estimated for an empirical return period of 269 years.

Further statistical modeling (particularly bivariate frequency analysis) is needed to improve the analysis of drought duration and magnitude variables, both randomly in nature and mutually correlated. Research is currently underway using a copula-based approach to test the bivariate frequency nature of the variables, with the objective of providing probabilities for a fixed duration for several magnitudes, or a fixed magnitude for several durations.

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