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Regional frequency analysis for mapping drought events in north-central Chile

by

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Abstract

Droughts are among the most important natural disasters, particularly in the arid and semiarid regions of the world. Proper management of droughts requires knowledge of the expected frequency of specific low magnitude precipitation totals for a variety of durations. Probabilistic approaches have often been used to estimate the average recurrence period of a given drought event. However, probabilistic model fitting by conventional methods, such as product moment or maximum likelihood in areas with low availability of long records often produces highly unreliable estimates. Recognizing the need for adequate estimates of return periods of severe droughts in the arid and semiarid region of Chile, a regional frequency analysis method based on L-moments (RFA-LM) was used for estimating and mapping drought frequency. Some adaptations to the existing procedures for forming homogeneous regions were found necessary. In addition, a new 3-parameter distribution, the Gaucho, which is a special case of the 4-parameter Kappa distribution, was introduced, and the analysis procedure was improved by the developments of two new software tools named L-RAP, to perform the RFA-LM analysis, and L-MAP, to map the resulting drought maps. Eight homogeneous sub-regions were delineated using the Gaucho distribution and used to construct return period maps for drought events with 80% and 40% precipitation of the normal. The study confirms the importance of a sub-regional homogeneity test, and the usefulness of the Gaucho distribution. The RFA-LM showed that droughts with a 40% precipitation of the normal have return periods that range from four years at the northern arid boundary of the study area to 22 years at the southern sub-humid boundary. The results demonstrate the need for different thresholds for declaring a drought than those currently in use for drought characterization in north-central Chile.

Keywords: L-moments; drought frequency; semiarid; precipitation; regional frequency analysis; Chile

1. Introduction

Meteorological droughts, the result of a precipitation deficit with respect to what is considered "normal" (Seth, 2003; Wilhite and Buchanan-Smith, 2005) are natural disasters which historically have affected large populations (and make up to 35% of those affected by natural disasters), often resulting in significant fatalities (50% of the mortality due to natural disasters), whereas 7% of world economic losses have been attributed to their occurrence (Below et al., 2007). These economic losses are likely to be higher because it is assumed that the indirect impacts are generally much more complex to evaluate than the direct consequences (Ponvert-Delisle et al., 2007).

Droughts can be characterized by their frequency, intensity and duration (Wilhite and Buchanan-Smith, 2005), as well as by the vulnerability of communities to drought impacts (Luers et al., 2003; Luers, 2005). Droughts can also be defined in agricultural terms based on a deficit in plant-available water, and in hydrological terms based on a deficit in streamflow. Drought frequency, both meteorological and hydrological, has been analyzed using a variety of probabilistic models, all of which allow probabilistic information present in the sample to be summarized (Chow et al., 1994; Demuth and Külls, 1997; Fernández and Vergara, 1998; Hisdal and Tallaksen, 2003; Loukas and Vasiliades, 2004; Serinaldi et al., 2009; Türk and Tatl, 2009). From the different probability approaches commonly used in hydrologic frequency assessment, the Index Flood Regional Frequency Analysis based on an L-moments procedure (RFA-LM), appears to provide the most robust estimates of meteorological drought frequencies (Hosking et al., 1985a). The advantages of regional frequency analysis, as well as L-moments have been recognized by several authors (Ciumara, 2007; Delicado and Goria, 2007; Hosking and Wallis, 1997; Kysely et al., 2010; Liou et al., 2008; Loucks and Van Beek, 2005; Mishra et al., 2007; Norbiato et al., 2007; Sankarasubramanian and Srinivasan, 1999; Stedinger et al., 1993).

In recent years, the RFA-LM methodology has been applied in preparing the U.S. Drought Atlas (Werick, 1995), meteorological drought analysis in northwestern Mexico (Hallack-Alegria and Watkins, 2007) and Turkey (Yurekli and Anli, 2008), hydrological drought analysis in southern Germany (Demuth and Kulls, 1997) and New Zealand (Pearson, 1995), and compared with other regionalization alternatives in European drought studies (Tallaksen and Hisdal, 1997; Tallaksen and Hisdal, 1999).

However, little work has been done on the application of RFA-LM for regional drought probability studies for arid and semiarid areas. These areas are the most vulnerable to drought because of the naturally limited precipitation supply. This is further exacerbated by their extreme spatial and temporal variability of precipitation (Kalma and Franks, 2003). Modarres (2009), for example, applied RFA-LM in the study of dry spells in the semiarid region of Iran. However, the author used at-site statistics in cluster and principal components analysis to check the presence of smaller homogeneous regions inside a previously well defined homogeneous region. This approach is inconsistent with the basic assumption of the index flood procedure where all sites within a homogeneous region have identical probability distribution (Reed et al., 1999; Stedinger et al., 1993) and the fact that at-sites statistics are not recommended to be used in homogeneous regions formation (Hosking and Wallis, 1997).

In another study, Vicente-Serrano (2006) applied RFA-LM to determine the best-fit distribution in the calculation of the Standardized Precipitation Index (SPI) for different time scales in the Iberian Peninsula. However, the author did not include confirmation of regional homogeneity in his analysis. He also based the choice of the best-fit distribution solely on the appearance of the L-moment ratio diagram. Hosking and Wallis (1997) and Peel et al. (2001) consider this approach insufficient for a proper choice of the best-fit distribution.

In the RFA-LM application to drought and other hydrological events, various criteria have been used to help form homogeneous regions. Some authors have included the use of cluster analysis (Burn and Goel, 2000), the region of influence (Gaál et al., 2007; Gaál and Kyselý, 2009), fuzzy logic (Chavochi and Soleiman, 2009), self-organizing maps (Lin and Chen, 2006) and the seasonality index (Kohnová et al., 2009) amongst the various schemes described by other authors (Burn and Goel, 2000; Reed et al., 1999). However, most of these methods are based on multivariate procedures, like cluster analysis, which do not reveal the physical reasons why these regions should be considered homogeneous (Clarke, 2010).

Although the RFA-LM methodology allows the incorporation of new general and flexible distribution models, homogeneity issues have not been previously explored in meteorological drought probability analysis of arid and semiarid regions.

Similarly, few studies have spatially mapped drought quantiles or return periods derived from the application of RFA-LM. Spatial mapping of drought characteristics using Geographic Information Systems (GIS) in combination with RFA-LM can be a powerful tool for drought risk management programs. Some studies have considered this aspect in the analysis of hydrological events, such as mapping the expected maximum short period rainfall for a given frequency in the U.S. (Schaefer et al., 2008; Wallis et al., 2007) and the mapping of the return period of dry spells in northeast Spain (Lana et al., 2008).

In this context, this paper proposes some modifications to the application of RFA-LM in the evaluation and mapping of meteorological drought frequency in north-central Chile. The robustness of extreme droughts estimation becomes critical in arid and semiarid regions, where the only available data source are short monthly precipitation records provided by a regionally scattered meteorological stations network. This study proposes a simplified procedure for homogeneous region formation, the adaptation of a specific case of the 4-parameter Kappa distribution, i.e. the 3-parameter Gaucho distribution, to obtain a best-fit regional probability distribution for drylands and tools to produce meteorological drought return period maps.

2. Methodology

2.1. Characteristics of the study area

2.1.1. Geographic characteristics

The study area is located in north-central Chile (Fig.1) and covers an area of 88,766 km^2. According to di Castri and Hajeck (1976) and Verbist et al. (2006), this area includes the arid regions at its northern boundary, with 9-10 dry months per year, and the semi-arid to sub humid regions on the southern boundary, with 5-6 dry months per year. Geographically, the region is located between latitudes 29º 01' and 34º 54' South and between longitudes 69º 50' and 72º 04' West. Elevation ranges from sea level to 6206 m at the highest part of the Andes.

2.1.2. Mean Annual Precipitation

Mean annual precipitation (MAP) (Fig.1) shows both a North-South and an East-West gradient, with a minimum of 50.6 mm in the far North and a maximum of 1055.6 mm at the southern edge of the study area. The extra-tropical frontal disturbances associated with the winter rains and the windward orographic rainfall formation due to the Andes explain the increase in the MAP from north to south and from the sea to the Andes (Rutllant, 2004). This spatial pattern and temporal dynamics are linked with the general circulation of the atmosphere in this area, and may be adversely affected by conditions of negative anomaly in sea surface temperatures associated with La Niña-ENSO phenomenon events, causing reductions of more than 60% of annual precipitation (Escobar and Aceituno, 1998; Quintana, 2000; Rutllant, 2004; Squeo et al., 2006; Verbist et al., 2010).

2.1.3. Data sources

For this study, 54 stations with daily precipitation records and 126 stations with monthly precipitation records were available. This provided a total of 180 meteorological stations distributed throughout the study area, with data provided by the Water General Directorate (DGA) and the Meteorological Directorate of Chile (DMC).

Precipitation records at daily stations were aggregated to produce monthly values, but only for months where there were complete daily records. If daily data were missing from a month, that month was not included in the analysis. The 180 stations had an average record length of 28.1 years, with a minimum of two years and a maximum of 75 years. 50% of the stations had 25 or fewer years-of-record.

In order to establish the final database for the RFA-LM procedure, we selected those stations that had a minimum record length of 15 years. This criterion was obtained using record curves, similar to those used by Bonnin et al. (2006). Selecting an appropriate minimum record length is important as it influences the number of stations for analysis as well as the total years of record, both affecting the reliability of the quantile estimates (Hosking and Wallis, 1997; Mishra et al., 2007). On this basis, 172 stations were selected for analysis.

2.2. Adapted RFA-LM procedure

The RFA-LM procedure used in this study was based on the methods proposed by Hosking and Wallis (1997) and the idea that the L-moments ratios L-Cv and L-skewness, defined as L-coefficient of variation and L-coefficient of skewness, respectively, are mapable quantities in their own right (Wallis et al., 2007). The five steps in the analysis procedure were:

1. data assembly, data screening and quality checking,
2. identification of homogeneous regions,

3. selection of the regional frequency distribution,
4. estimation of distribution parameters and the quantile function, and
5. spatial mapping of L-moment and drought characteristics.

These five steps are presented below.

2.2.1. Stage 1: Data screening and quality checking

Considerable efforts were made in the screening and quality checking of precipitation data, which aimed at eliminating false values associated with a wide variety of data measurement, recording and transcription errors. Special emphasis was given to the confirmation of the basic assumptions of homogeneity, using double mass curve analysis (WMO, 1994); stationarity, using linear regression analysis; and autocorrelation, using the Lag-1 test for serial independence (Wallis et al., 2007).

As a quality control tool, the discordancy measure (Di) from Hosking and Wallis (1997) was used to identify those stations for which sample L-moments were significantly different from the observed pattern of the other sites within the region.

2.2.2. Stage 2: Formation and acceptance of homogeneous sub-regions

2.2.2.1. Formation of candidate homogeneous sub-regions

A homogeneous sub-region is herein defined as a group of sites (stations) whose data, after rescaling by the at-site mean, can be described by a common probability distribution (Hosking and Wallis, 1997; Stedinger et al., 1993; Brath et al., 2001). This is often termed as the Index Flood (Stedinger et al., 1993) approach to regional frequency analysis. In addition, the site data must satisfy the homogeneity criterion H1 originally defined by Hosking and Wallis (1997).

A heterogeneous super-region is herein defined as a geographic area composed of homogeneous sub-regions whose data can be described by the same probability distribution. Depending on the complexity of the phenomenon being analyzed, the study area may be comprised of one or more heterogeneous super-regions.

In this paper we propose using a seasonality index and the magnitude of MAP as criteria for forming homogeneous sub-regions. A similar approach was suggested by Kohnová et al. (2009), but using measures of seasonality in regional stream flow frequency analysis.

The procedure we used was thus as follows:

a) For each station, a Seasonality Index (SI), the Julian Mean Day (JMD) and MAP were calculated. The SI and JMD calculations are described by Dingman (2001) and Schaefer et al. (2008) and are based on circular statistics which yield the average day of occurrence, analogous to the arithmetic mean for dates, and SI, similar to a standardized measure of variation. The SI takes values between 0 and 1. Values near 0 indicate a wide variation in the time-of-year of occurrence, while values close to 1 indicate small variation in the time-of-year of occurrence and therefore a high seasonal concentration of data (Schaefer et al., 2008).

b) Based on SI values and their corresponding precipitation histograms for a large set of precipitation stations, a criterion for pooling stations into homogeneous sub-regions was defined: Group 1, stations with SI from 0 to 0.2; Group 2, with SI between 0.2 and 0.6; and Group 3 with SI greater than 0.6. This grouping ensures that stations that have different rainfall forming processes are separated, since no distribution can fit to station data belonging to two or more of these different groups simultaneously.

c) In the event that stations are all within the same SI range, they can be further partitioned according to their JMD values. This is appropriate because there may be stations with similar SI values but whose rainfall concentration occurs at different times of the year (areas with rainfall concentrated in summer and others with rainfall concentrated in winter which can have different moisture sources, storm intensities and durations).

d) Finally, stations with similar SI and JMD values can be further partitioned into candidate homogeneous sub-regions according to the magnitude of MAP. This approach is based on the finding that the shape of the regional probability distribution is often related to the magnitude of MAP. Specifically, it is expected that data from semi-arid regions show greater variability, higher skewness and different probability distribution shapes than data from more humid regions, as has been indicated by several authors (Eriyagama et al., 2009; Fuentes et al., 1988; Gastó, 1966; Kalma and Franks, 2003; Le Houérou, 1988; Schaefer et al., 2008). To accommodate this behavior, stations were ordered from lowest to highest magnitude of MAP and grouped to form a suitable number of sub-regions with similar sample size.

e) Homogeneous sub-regions need not be geographically continuous (Hosking and Wallis, 1997), so that no stations were forced to belong to a particular sub-region because of geographical proximity.

2.2.2.2. Acceptance of candidate homogenous sub-regions

The homogeneity of each sub-region was confirmed using the H1 heterogeneity measure of Hosking and Wallis (1997). The H2 heterogeneity measure was not used because it has proven to lack statistical power (Viglione et al., 2007).

A sub-region was accepted as homogeneous where $H1<2$, possibly heterogeneous with $2<H1<3$ and as a heterogeneous, if $H1>3$. The selection of these thresholds was based on recommendations from Wallis et al. (2007) which account for site-to-site variability resulting from data measurement and recording errors in addition to statistical variability.

2.2.3. Stage 3: Selection of regional probability distribution

The selection of the best-fit regional probability distribution function was based on screening L-moment ratio diagrams. The final decision was based on the $Z^{|DIST|}$ goodness-of-fit test described by Hosking and Wallis (1997) as applied to all of the homogeneous sub-regions within a heterogeneous super-region.

The distributions that were examined included the Generalized Pareto, Generalized Extreme Value, Generalized Normal, Pearson Type III, Generalized Logistic, and the 4-parameter Kappa distribution (4-p-Kappa) as well as the 3-parameter Gaucho distribution described in detail below. The application of L-moments to estimate the parameters of these and other distributions has been described by several authors (Abdul-Moniem and Selim, 2009; Delicado and Goria, 2007; Kundu, 2001; Hosking and Wallis, 1997; Shawky and Abu-Zinadah, 2009).

In this study, we also proposed a new distribution based on a modification to the 4-p-Kappa distribution described by Hosking (1994), in which the second shape parameter, *h*, was set to a value of 0.50. This special case of the 4-p-Kappa distribution is called the "Gaucho distribution", whose inverse function is as follows:

$$q(F) = \xi + \frac{\alpha}{\kappa}\left\{1 - \left(\frac{1 - F^{0.50}}{0.50}\right)^{\kappa}\right\} \qquad (Eq.1)$$

where $q(F)$ is the Gaucho quantile function, F is the non-exceedance probability for the desired quantile, ξ and α are the location and scale parameters, κ is the first shape parameter, and the second shape parameter *h* for the 4-p-Kappa distribution is set to a value of 0.50.

Thus, the Gaucho distribution constitutes a three-parameter distribution which can be represented in an L-moments ratio diagram as bisecting the space between the Generalized Pareto and Generalized Extreme Value distributions.

Although several probability distributions might be statistically acceptable for each homogeneous sub-region based on the $Z^{|DIST|}$ goodness-of-fit measure, the adopted regional probability distribution was selected as the distribution most frequently accepted by the collection of homogeneous sub-regions within the heterogeneous super-region.

2.2.4. Stage 4: Estimation of distribution parameters and quantiles

After the regional probability distribution was selected, the distribution parameters for each homogeneous sub-region were determined by the method of L-moments as described by Hosking and Wallis (1997). The inverse function could then be expressed in dimensionless form (Eq. 2), which is termed a regional growth curve (Hosking and Wallis, 1997; Stedinger et al., 1993):

$$\hat{Q}_i(F) = \hat{\mu}_i \hat{q}(F) \qquad Eq.2$$

where $\hat{Q}_i(F)$ is the quantile function for station i, $\hat{\mu}_i$ is the at-site mean for station i, $\hat{q}(F)$ is the regional growth curve.

Site-specific quantile estimates for annual precipitation were obtained by multiplying the regional growth curve by the at-site value of mean annual precipitation (MAP). For the case of sites with station data, the MAP value obtained from the station data was used to scale the regional growth curve. For ungauged sites, the at-site MAP value was estimated using a topoclimatics interpolation method as described by Morales et al. (2006).

2.2.5. Stage 5: Mapping

Spatial mapping of various proportions of annual precipitation is helpful in depicting the frequency of precipitation deficits throughout the study area. Color-shaded maps were generated depicting the return periods for values of 80% and 60% of mean annual precipitation (20% and 40% precipitation deficits). This is consistent with the concept of defining drought thresholds as some percentage of the most recent 30-year climatic normal for mean annual precipitation (Quiring, 2009a).

To construct the maps, we first developed relationships between L-moment ratios and MAP for the homogeneous sub-regions. This is an approach used in several studies that have shown that MAP is often a good explanatory variable for describing the spatial variability of the L-moment ratios (Baldassarre et al., 2006; Schaefer et al., 2008; Wallis et al., 2007).

The procedures for spatial mapping of quantile estimates and return periods using relationships between L-moment ratios and MAP are described in Wallis et al. (2007). These spatial mapping procedures consisted of:

a) Determining predictive relationships between sub-regional values of L-Cv and MAP, and L-skewness and MAP such as described by Eq. 3. We also created two additional “extreme sub-regions” to facilitate predictions and mapping near the extreme ends of the available data. These “extreme sub-regions” were obtained by combining the eight stations with least MAP, and the eight stations with the highest MAP to form two additional sub-regions. Regional values of the L-moment ratios were computed for these two sub-regions as described previously. The function selected for describing the relationship between L-moment ratios and MAP was as follows :

$$\text{L-Moment ratio} = \alpha\, e^{-\beta(MAP)} + \delta \qquad (Eq.3)$$

where α, β and δ are fitting parameters. Their values were determined by least-squares optimization using Excel's Solver tool. As a measure of goodness-of-fit, the RMSE and Standardised RMSE ($RMSE_S$) were used (Schaefer et al., 2008).

b) A raster grid map of MAP for the study area was constructed by multiple regression analysis using a topoclimatics information procedure as described by Morales et al. (2006).

c) From the gridded map of mean annual precipitation, and using the prediction function (Eq. 3), L-Cv and L-skewness values were generated for each cell of the raster map of MAP.

d) Maps of drought return periods were generated by first solving for the distribution parameters for each grid-cell based on grid-cell values of L-Cv and L-skewness, and then solving for the non-exceedance probability (*F*) using the cumulative distribution function for the selected regional probability distribution.

2.3. Analysis tools

To facilitate application of the RFA-LM methodology, the L-RAP software package was utilized (Schaefer, 2008). L-RAP has a Windows user-interface and executes the FORTRAN routines of Hosking (2005) which provides a number of advantages over other RFA-LM computational tools developed by other authors (Asquith, 2009; Hosking, 2009a; Hosking, 2009b; Karvanen, 2009; Viglione, 2009). These advantages include:

a) It has a friendly graphical user interface, which facilitates use by analysts not familiar with the use of FORTRAN or other routines.

b) L-RAP proceeds step-by-step through each of the stages associated with RFA-LM. This begins with an EXCEL template for data import, data quality control, checking of the assumptions of stationarity and independence, computation of the SI, JMD, Di and heterogeneity indices, computation of goodness-of-fit measures for selection of the regional probability distribution, computation of distribution parameters and quantiles.

c) It generates L-moment diagrams, quantiles, graphs, and summary data from each station presented graphically, as histograms and probability-plots.

d) It permits direct editing of the database which is stored in the internal binary format of L-RAP, which is essential for iteratively adding and eliminating stations to proposed homogeneous subregions.

For the preparation of the return period maps, we developed a software tool called L-MAP (Verbist, 2010). It is based on the L-RAP algorithms, and it can import an IDRISI binary type format base map and use it for spatial mapping of L-moment ratios, return periods and precipitation quantiles.

3. Results

3.1. Stage 1: Data screening, preparation and assumptions checking

Table 1 lists summary statistics for annual precipitation data from the 172 stations. These stations have an average record length of 29.2 years and totaled 5015 station-years of record. This dataset yielded an average MAP of 359.4 mm, with a minimum of 50.6 mm and a maximum of 1055.6 mm. Tests for stationarity and serial independence were conducted on the collection of 172 stations, and showed that most stations (94%) passed the test for stationarity and serial independence (99%). As such, the time-series of annual precipitation data were deemed to be stationary and serial independent.

3.2. Stage 2: Formation and acceptance of homogeneous sub-regions

3.2.1. Analysis of seasonality and MAP for forming homogeneous sub-regions

A SI and JMD were computed for the time-series data of annual precipitation at each of the 172 stations. Frequency histograms of SI and JMD as well as scatterplots and linear regression analysis between these variables and MAP are shown in Fig. 2. The purpose of this analysis was to detect any changes in SI and JMD along a precipitation gradient which increases from the driest (in the North) to the wettest portions of the study area in the South. The SI showed an average of 0.87, with a minimum of 0.72 and a maximum of 0.94. This implies a high concentration of rainfall in a few months. In fact, Aceituno (1992) showed that in Chile, between latitudes 30º and 35º S, rainfall occurs mainly in the winter months of June to August.

Huanta, Ramadilla, San Gabriel and Farellones Ski stations exhibit the four lowest SI values. These four stations are located in mid-mountain areas of the Andes. It is possible that these stations receive summer rainfall of convective origin, affecting their seasonality, although Garreaud and Rutllant (1997) indicated that summer rainfall does not represent more than 5% of the annual precipitation total.

The JMD showed an average of day 180 with a minimum and a maximum of day 157 and day 191 respectively, and a small coefficient of variation of 2.6%. That is, the rainy season in Chile is concentrated around the 30th of June (day 180). The lower values of JMD of two stations, one of which is also the Ramadilla station, could suggest different behavior in their seasonality of precipitation or problems with data quality. The discordancy measure Di will be used in a later step to assist in determining if these two stations should be included or excluded from the analysis of the study area.

Verbist et al. (2006) have shown that the number of months with precipitation increases from north-to-south in the study area as does the precipitation amount in the wettest month. However, Figs. 2b and 2d show that the SI and JMD do not vary with mean annual precipitation from north-to-south across the study area. This finding is consistent with the effect of the atmospheric general circulation in Chile where rainfall is concentrated in the winter season and interannual variability is exclusively associated to a gradient of annual precipitation, mainly in the north-south direction (Fuentes et al., 1988). Thus, the entire study area can be considered to have the same seasonality of precipitation.

These findings indicate that the study area is comprised of one heterogeneous super-region containing several homogeneous sub-regions. The homogeneous sub-regions were formed based on grouping of stations within a similar range of MAP.

3.2.2. Choice of the number of homogeneous sub-regions

The determination of the number of candidate sub-regions was based on finding a balance between providing a sufficient number of sub-regions to develop a reliable predictor equation for L-Cv and L-Skewness relationships for spatial mapping (Eq. 3), and having sufficient stations within a sub-region to reliably estimate regional values of L-Cv and L-skewness.

Using this criteria, and considering that for a homogeneous sub-region there is little advantage in having more than 20 stations (Hosking and Wallis, 1997), eight homogeneous sub-regions were defined. This number of subregions allows for a sufficient optimization of Eq. 3 using the least square difference technique. Within the eight sub-regions, the stations were assigned according to the magnitude of MAP arranged in ascending order. Each sub-region had an average of 21 stations and 638 station-years of record.

As suggested by Schaefer et al. (2008) and Wallis et al. (2007), forming homogeneous regions is an iterative process. Table 2 presents the eight homogeneous sub-regions, obtained after three iterations. These iterations resulted in the elimination of four stations that were discordant and moving three stations from one sub-region to another due to high discordancy. Table 2 also lists sub-regions 9 and 10 that were formed at the extreme ends of the range of MAP to assist in describing the predictor equation for L-Cv and L-skewness (Eq. 3).

Computation of the heterogeneity measure H1 showed the final eight sub-regions to be acceptably homogeneous. Of the 168 stations included in the eight homogeneous sub-regions, only three stations (each in different sub-regions) had a discordancy value above the Di critical value of 3 (Station Alicahue: Di = 3.9, Station Ramadilla: Di = 3.7 and Station San Antonio: Di = 3.4). All stations are mildly discordant and it was decided to keep them as part of the collection of stations for the sub-regions.

3.3. Stage 3: Selection of regional probability distribution

As a first step in selecting the best-fit regional probability distribution by using graphical methods, including the L-moment ratio diagram (Peel et al., 2001; Vogel and Fennessey, 1993), Fig. 3 shows the L-Skewness vs L-Kurtosis ratio diagrams generated by L-RAP for the eight homogeneous sub-regions. It is seen that the center of the cloud of L-skewness and L-kurtosis pairs for all sub-regions, is located near the Gaucho distribution curve. However, a given sub-region may also plot close to the GEV distribution or Pearson Type III. Less proximity was found to the Generalized Pareto distribution and even less to the Generalized Logistic. This suggests that the Gaucho distribution is a good fit to the observed data for the collection of sub-regions.

However, as Hosking and Wallis (1997) and Peel et al. (2001) suggest, visual examination of the L-moment ratio diagram should not be the sole criterion when choosing the best-fit distribution, but should include a goodness-of-fit measure for identification of acceptable distributions. Accordingly, Table 2 presents the best-fit distributions for the eight proposed homogeneous sub-regions based on the $Z^{|DIST|} < 1.64$ goodness-of-fit test. The distributions, in order of highest to lowest goodness-of-fit were Gaucho, Pearson Type III, Generalized Normal, Generalized Extreme Value and Generalized Pareto. The only common distribution to the eight homogeneous sub-regions was the Gaucho distribution. This confirms the point made by Hosking and Wallis (1997) that the 4-p-Kappa distribution, source of the Gaucho distribution, has a high degree of flexibility to adapt to a variety of distribution models. The 4-p-Kappa distribution is a generalization of a number of other commonly used distributions in hydrology, like the generalized logistic, the generalized extreme-value or the generalized Pareto (Finney, 2004; Hosking, 1994).

3.2.4. Stage 4: Parameter and quantiles estimation

Table 3 presents the values of the parameters of location ξ, scale α, and the shapes κ and h (set to 0.50), of the Gaucho distribution. It also includes the values of the same four parameters obtained by fitting the 4-p-Kappa distribution. Between the northern arid boundary and the southern subhumid boundary of the study area, the location parameter ξ increased from 0.43 to 0.67, α decreased from 0.69 to 0.59 and κ increased from -0.03 to 0.36. Thus, the Gaucho distribution has enough flexibility to adapt to the behavior of the annual precipitation data across the study area. For the 4-p-Kappa distribution, ξ increased from 0.25 to 0.75, α decreased from 0.87 to 0.47, κ increased from 0.07 to 0.25 and h decreased from 0.82 to 0.28.

The results in Table 3 indicate a minor change in the shape of the regional probability distribution, closer to the Generalized Pareto on the northern boundary to a GEV or Generalized Normal near the southern boundary. The average 4-p-Kappa h value for the eight homogeneous sub-regions was 0.45, which is very close to the value h = 0.50 set for the Gaucho distribution.

In addition, the κ parameter values of the eight sub-regions, the value h = 0.50 in the case of the Gaucho distribution, and the h parameter values of the eight sub-regions in the case of the 4-p-Kappa distribution fit, are all located near the center of the parameter space that ensures the existence of the L-moments (Hosking, 1994; Winchester, 2000). They are also located in a region of the parameter space in which the bias and RMSE in quantile estimation using L-moments is significantly less than that obtained with the maximum likelihood estimation method (Dupuis and Winchester, 2001). This suggests that the RFA-LM produces more robust estimates in the study area than those obtained by conventional methods based on at-site and/or using maximum likelihood or product-moment estimation methods.

Table 4 lists the regional quantiles for each of the eight homogeneous sub-regions, obtained from the Gaucho distribution. It can be seen that from sub-region 1 to sub-region 8, there is a reduction in the variability in quantile estimates. This is related to the reduction of the Gaucho distribution scale parameter α from 0.69 to 0.59 in the North-South direction, and is associated with a decreasing trend from North to South of L-Cv, L-kurtosis and L-skewness, as shown in Table 2. In this way, more frequent extremes can be expected in the drier areas than in the wetter climates of the study area. This behavior is similar to that described by Schaefer et al. (2008) and Wallis et al. (2007). It also coincides with the fact that there is a high interannual rainfall variability within arid and semiarid regions (Kalma and Franks, 2003) and is fully consistent with the analysis of dry year frequency for the Chilean territory made by Gastó (1966). The latter, categorizing the years from very dry to very wet, found a higher frequency of dry or very dry years (42% of all years) in the northern arid zone near the study area and a lower frequency (27%) in the southern, subhumid regions. These results indicate the importance of selecting the appropriate probability distribution in the analysis of annual meteorological drought, at least in semi-arid regions with high gradients of interannual variability from dry to more humid zones.

Some authors, although implementing the RFA-LM for distribution fitting of annual precipitation in their study areas with similar or higher precipitation gradients than this study (Yue and Hashin, 2010), or placed in other semiarid regions (Vicente-Serrano, 2006), did not confirm the homogeneity assumption in their analysis. This can result in a mis-specification of the regional distribution as well as an increase in the bias of the estimates solely due to using a heterogeneous region, which is inconsistent with the basic assumption of the index flood regional frequency analysis (Stedinger et al., 1993; Reed et al., 1999).

3.2.5. Stage 5: Drought return period mapping

3.2.5.1. Predictor equations for spatial mapping of L-Cv and L-skewness

Plots of the predictor equations for L-moment ratios as a function of MAP, together with the parameters and goodness-of-fit measures are shown in Fig. 4. The general goodness-of-fit for L-Cv and L-skewness is visually evident. Greater variability is seen for the regional L-kurtosis values, which is a characteristic inherent to the higher moments. The solutions for L-Cv and L-skewness are particularly important because the quality of those relationships largely determines the reliability of quantile estimates for 3-parameter probability distributions such as the Gaucho distribution.

3.2.5.2. Annual meteorological drought return period map

The L-Cv and L-skewness maps of the study area are shown in Fig. 5. The L-kurtosis map is not included, because the Gaucho distribution has only three parameters and can be calculated only from L-moment 1 (MAP), L-Cv and L-skewness. There is a decreasing trend of L-Cv and L-skewness (derived from the best-fit curves previously obtained in Fig. 4) from the northern edge to the southern edge of the study area. The decrease in L-Cv and L-skewness along the North-South axis is also associated with a decrease, in the same direction, of the variability in the regional growth curve in the left tail and especially the right tail as was seen in Table 2. Therefore, if the comparison is made with respect to the average value of precipitation, as the Index Flood scaling factor, the probability of very dry or wet years is greater at the northern edge and is lower on the southern edge of the study area. For example, a 0.4 quantile of the regional growth curve (equivalent to 40% of normal) had a probability of exceedance of 0.23 in sub-region 1, equivalent to a return period of approximately four years. In contrast, the same quantile in sub-region 8, had a probability of exceedance of 0.05, equivalent to a return period of about 18 years. In the upper tail of the regional growth curve the difference is even larger: a quantile of 2, equivalent to twice the MAP, in sub-region 8 is seen on average once every 100 years, whereas in sub-region 1, it happens on average once every 10 years.

Drought return period maps for 80% and 40% of the normal are presented in Figs. 6a and 6b respectively. The results indicate that, on average, the 80%-of-the-normal drought has similar return periods along the study area, with a minimum of two years around the northern edge and about three years at the southern edge. These similarities are due to the small differences between the quantiles of the regional growth curves around the central values of the distribution.

In contrast, a 40%-of the–normal drought occurs between three and four years on average at the northern edge and every 22 years at the southern one. That is, higher aridity implies more recurrence of extreme annual drought events. The spatial distribution of drought frequency agrees with previous studies that analyzed the frequency of dry years in Chile (Gastó, 1966).

The map also allows us to appreciate a decreasing frequency component from coast to mountains, associated with increased precipitation in that direction. This means that coastal drylands have a greater frequency of droughts than foothill drylands. Between parallels 33º and 35º S a distinct pattern in the frequency can also be seen, compared with the area north of latitude 33º S. This is because the terrain topography changes from the type known as transverse valleys, between parallels 29º and 33º S, to the type referred to as longitudinal valleys, southwards of 33° S. The orographic effect that influences the distribution of annual precipitation in that location, which increases to the West in the coastal mountain range, is reduced again in the longitudinal valleys, and increases again towards the East, towards the mountains of the Andes (Falvey and Garreaud, 2007). This pattern is reflected in the spatial distribution of the drought return period, where higher frequencies enter into the center of the valley around the parallel 33.4º S. The map also allows us to determine locations with greater frequency of droughts, which can be used in the preparation of drought vulnerability maps (Luers, 2005) or risk maps (Wilhite and Buchanan-Smith, 2005), useful for decision making support and climate risk management. For example, while the years with annual precipitation deficits are more common toward the north, economically important rain-fed farming presents a diametrically opposite distribution. The North is predominantly associated with livestock raising goats on farmers communal land (MINAGRI-INDAP-PRODECOP, 2001), while rainfed agriculture is much more developed towards the southern boundary. There are more options for cropping, and greater land area is used for agricultural crops, including wheat, and for improved natural grasslands and sown pastures for raising sheep and cattle. Under these conditions, a drought of 40%--of-the-normal does not cause the same impact as in the North. Therefore, it is important to define different drought thresholds throughout the study area. This contrasts with the drought definition established nowadays by Chilean legislation, which uses for a significant proportion of the study area a single Percent to Normal and a single accumulated precipitation return period value to define extreme water scarcity events (DGA, 1984). In this regard, as indicated by Steineman et al. (2005), the drought definition used in this study does not consider the different impact that the same precipitation deficit level has in different regions, but it has the advantage of obtaining return periods for a given quantile, and it is the end user who can turn that quantile to the drought indicator of choice. In addition, the percentage with respect to the normal is a widely adopted drought indicator that can be related to quantiles and percentiles, and is considered one of the best available drought indicators, as a complement to the commonly used Standardized Precipitation Index (Keyantash and Dracup, 2002; Quiring, 2009a,b).

The results of this study also enable us to determining the frequency of the most important droughts, i.e. those reported to have had the greatest economic impacts in north-central Chile, such as e.g., the 1968 and 1997 droughts (Espinoza and Hajeck, 1988; Fernández et al., 1997). In those years, annual precipitation in north-central Chile was between 20-30% of a normal year. Based on the regional growth curves presented in Table 4, a quantile of

0.3 is equivalent to a 30% drought, and has a return period of approximately six years at the northern edge, 24 years in the central study area and 68 years in the far South. Therefore, it is important that legislation considers the enormous variability in the definition of drought being used throughout this study area.

Finally, if one includes also the concept of sensitivity, adaptive capacity and vulnerability (Luers et al., 2003), along with the frequency of occurrence of drought as a stressful event, then the risk or vulnerability of the area should have a high spatial variability along the gradient of mean annual rainfall.

4. Conclusions

In this study, a methodology was developed to use a RFA-LM procedure for estimating the spatial distribution of drought frequency in northern-central Chile, in a transition between arid and sub-humid areas of the country. Based solely on the use of monthly precipitation records, it was possible to identify homogeneous sub-regions along the study area, which were fitted by different probability distribution models. The model that best fit the entire area was the Gaucho distribution, which was defined in this study as a special case of the 4-p-Kappa distribution. The use of this model allows identifying a gradient of drought frequency along the study area which depends on the considered drought level. Thus, while the frequencies of 80%-of-the-normal droughts are relatively similar throughout the area, those of 40%-of-the-normal result in differences in about four orders of magnitude. A drought defined as 30%-of-the-normal can have differences of up to 10 orders of magnitude between the northern arid region and the southern subhumid area. Given the high frequency of these extreme droughts at the northern edge of the study area, which is nearly six years, they might better be considered as a structural condition of the region rather than extreme events. As such, it requires a change of management strategy to deal with low precipitation events in this area on a permanent basis.

The results also indicate the importance of a homogeneity check, for proper probability distribution selection, especially in drylands along annual precipitation gradients. For example, a proper selection of the distribution model used in drought indices based on frequency analysis, such as the widely used Standardized Precipitation Index, could be critical for extreme drought events detection, especially for annual values in arid zones based on this drought index. The proposed methodology allows more robust estimation of quantiles compared with conventional methods. Its representation in terms of practical drought frequency maps can be used by water resource managers for decision making. The maps obtained indicate the need to consider the use of different thresholds of drought throughout the study area, which, together with drought vulnerability maps, could generate drought risk maps to guide differentiated strategies in drought management along the North-South axis of central Chile.

On the other hand, when drought frequency has to be determined for some specific drought events in ungauged sites, the procedure presented in this study will yield better estimates than any other available method. With this procedure, there is no need to have long time series of station data to develop a drought monitoring network, as in an at-site approach, because the RFA-LM analysis allows pooling stations to construct a stronger basis for selecting correct distributions and their quantiles. Therefore, this methodology should be of practical value for these regions that lack abundant climate data sets, but suffer from high drought frequency, as is common in arid and semi-arid regions throughout the world.

Acknowledgements

The authors wish to express their appreciation to the Government of Flanders, the UNESCO International Hydrological Programme, the IWR of the U.S. Army Corps of Engineers, and the Water Center for Arid and Semiarid Zones of Latin America and the Caribbean (CAZALAC). Also, and especially, we are grateful to the General Water Directorate of Chile and the Chilean Meteorological Office, who provided all necessary climate information for this analysis.

Appendix – Brief overview of the RFA-LM methodology development

Many practical problems require the fitting of a probability distribution to a data sample. In many fields of application the available data do not consist of a single sample, but a set of samples drawn from similar sites that can be expected to have similar probability distributions. The distribution for one sample can be more accurately estimated by using information, not only from that sample, but also from the other related samples. In environmental sciences, data samples are typically measurements of the same kind of data made at different sites, and the process of using data from several sites to estimate the frequency distribution is known as regional frequency analysis.

In the early 1970s, there was a growing awareness among hydrologists that annual maximum stream flow data, although commonly modeled by the Gumbel distribution, often had higher skewness than was consistent with that distribution. Moment statistics were widely used as the basis for identifying and fitting frequency distributions, but to use them effectively required knowledge of their sampling properties in small samples. A massive (for the time) computational effort using simulated data was performed by Wallis et al. (1974). It revealed some unpleasant properties of moment statistics: high bias and algebraic boundedness.

In hydrology and meteorology, having a sequence of values observed at a site that is normally distributed is rare, while skewed distributions are quite commonly observed. Unfortunately the estimate of the skew coefficient, G, is mathematically constrained, a fact which has been known since 1944, but frequently forgotten or ignored by practitioners. For instance, consider samples of length 30 taken from a Type I Extreme Value Distribution with mean 2600, standard deviation 800 and skewness 10; the constraint on the estimate of the skew coefficient is solely a function of the sample size, n:

$$G = \frac{n-2}{\sqrt{n-1}} \qquad (Eq.4)$$

The maximum value G is therefore 5.2 for a sample of 30 when the true skewness coefficient was 10.

Attempting to try and select the true parent distribution from single samples by using a conventional goodness-of-fit measure can be perilous to say the least. In Table 5 the results are given of an experiment where samples from an Extreme Value type I (EV I) distribution were generated and with the best fit being chosen based upon minimum mean squared deviation for three distribution: EV I, Log Normal, and the Normal distribution. Note that even with a sample size of 90 the correct distribution was chosen only 40% of the time.

In contrast, the higher L–-moments are not constrained by sample size and their estimates have small bias and small range of -1 to +1. This is a strong argument for regionalization, and if the region is homogeneous we can expect that the extreme quantile estimates obtained will be better than those made with any at-site estimator. Matalas et al. (1975) went on to establish the phenomenon of ‘separation of skewness’, which is that for annual maximum stream flow data the relationship between the mean and the standard deviation of regional estimates of skewness for historical flood sequences is not compatible with the relations derived from several well known distributions. Separation can be explained by ‘mixed distributions’ (Wallis et al., 1977) – regional heterogeneity in our present terminology – or if the frequency distribution of stream flow has a longer tail than those of the distributions commonly used in the 1970s. In particular, the Wakeby distribution, which was devised by H.A. Thomas Jr. (personal communication to J.R. Wallis, 1976), does not exhibit the phenomenon of separation (Landwehr et al., 1978). It is hard to estimate by conventional methods such as maximum likelihood or the method of moments, and the desirability of obtaining closed-form estimates of Wakeby parameters led Greenwood et al., (1979) to devise Probability Weighted Moments, PWMs. They were found to perform well for other distributions (Landwehr et al., 1979; Hosking et al., 1985b; Hosking and Wallis, 1987), but were hard to interpret. Later, Hosking (1990) found that certain linear combinations of PWMs, which he called ‘L-moments’, could be interpreted as measures of the location, scale, and shape of probability distributions and formed the basis for a comprehensive theory of the description, identification, and estimation of distributions.

The modern use of the index-flood procedure stems from Wallis (1981, 1982), who used it in conjunction with PWMs and the Wakeby distribution as a method of estimating quantiles in the extreme upper tail of the frequency distribution. Comparative studies showed that this ‘WAK/PWM’ algorithm and analogs in which other distributions were fitted, outperformed the quantile estimation procedures recommended in the U.K. Flood Studies Report (Hosking et al., 1985a) and the U.S. ‘Bulletin 17’ (Wallis and Wood, 1985). Later work investigated the performance of this index flood procedure in the presence of archeological and historical data (Hosking and Wallis, 1986a,b), regional heterogeneity (Lettenmaier et al., 1987), and intersite dependence (Hosking and Wallis, 1988). The practical utility of regional frequency analysis using this index-flood procedure, however, still required subjective judgment at the stages of formation of the regions and choice of an appropriate frequency distribution for each region; statistics to assist with these judgments were developed by Hosking and Wallis (1993).

The first of these statistics, called D_i for Discordancy, measured the dispersion of the sample l-moment ratios (L-Cv, L-Skewness, and L-Kurtosis) of a site in three-dimensional space. A group of sites will yield a cloud of such points and any point that is far from the center of the cloud will be flagged as discordant. The formal definition can be found on page 46 of Hosking and Wallis (1997).

The second statistic, H1, estimates the degree of heterogeneity in a group of sites to assess whether the sites might reasonably be treated as a homogeneous region. Specifically, the heterogeneity measure compares the between-site variations in sample L-moments for the group of sites with what would be expected for a homogeneous region. The formal definition can be found on page 63 of Hosking and Wallis (1997). Once a homogeneous region has been verified one can proceed to the next step, identifying the most likely regional distribution.

The third statistic, $Z^{|DIST|}$, is used to test whether any given distribution fits the regional data acceptably closely. The formal definition can be found on page 81 of Hosking and Wallis (1997). Several distributions may fit the regional data quite adequately. Luckily, when this has been observed, the distributions chosen have great similarity in their CDF’s and departure is often only of importance at very extreme quantiles.

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Figure Captions

Figure 1 Map of the study area (north-central Chile) indicating mean annual precipitation and the spatial distribution of the 180 raingauge stations.

Figure 2 Histogram and descriptive statistics of (a) Seasonality Index and (c) Julian Mean Day and scatterplots and linear regression equations between (b) Seasonality Index and Mean Annual Precipitation and (d) between Julian Mean Day and Mean Annual Precipitation.

Figure 3 L-moment ratio diagrams for L-skewness vs. L-kurtosis for homogeneous sub-regions 1 to 8.

Figure 4 Best fit curves for (a) L-Cv versus Mean Annual Precipitation, (b) L-skewness vs. Mean Annual Precipitation and (c) L-kurtosis vs. Mean Annual Precipitation.

Figure 5 Map of spatial distribution over the study area (north-central Chile) of (a) L-Cv and (b) L-skewness..

Figure 6 Map of the drought return period for (a) 80% of average precipitation and (b) 40% of average precipitation.