Drought meteorological monitoring network design for the Reconnaissance Drought Index (RDI)

Tsakiris G., Nalbantis I., Pangalou D., Tigkas D., Vangelis H.

in

López-Francos A. (ed.).
Drought management: scientific and technological innovations

Zaragoza : CIHEAM
Options Méditerranéennes : Série A. Séminaires Méditerranéens; n. 80

2008
pages 57-62

Drought meteorological monitoring network design for the Reconnaissance Drought Index (RDI)

G. Tsakiris, I. Nalbantis, D. Pangalou, D. Tigkas and H. Vangelis
National Technical University of Athens,
Lab. of Reclamation Works & Water Resources Management,
Centre for the Assessment of Natural Hazards & Proactive Planning,
9, Iroon Polytechniou, 15780 Athens, Greece
email: water@survey.ntua.gr

SUMMARY – Several meteorological drought indices have been used in the past to assess drought severity. Most of the indices use monthly precipitation data (e.g. SPI) and in some cases additionally monthly potential evapotranspiration data (e.g. RDI). The objective of this paper is to present the new Reconnaissance Drought Index and its requirements and also to specify the requirements of a meteorological monitoring network aiming at providing data for the calculation of such indices. From the methodologies examined the one based on geostatistical tools such as the kriging method was tailored and successfully used for the purpose of drought monitoring.

Key words: Reconnaissance Drought Index, SPI, drought monitoring, drought assessment, Mediterranean basin.

Introduction

Traditionally drought indices have been used for drought severity assessment. Numerous indices have been presented in the last four decades. Recently, a new promising meteorological drought index, the Reconnaissance Drought Index (RDI) has been proposed. This index makes use of precipitation and potential evapotranspiration simultaneously. As a result, drought monitoring using the RDI has to be based upon a suitable precipitation gauge network and a network for monitoring evapotranspiration. As explained in the third section below, the precipitation network is the most critical component of a drought monitoring system, which uses the RDI. Hence, designing such a network is the main task in setting up a drought monitoring system.

Existing methodologies for designing precipitation networks have to be analysed and evaluated in order to select the most appropriate of them for drought assessment. Moreover, these are not directly applicable to the specific case without prior adaptation.

The purpose of this paper is two-fold: (i) to give a short description of the RDI in the form of three variants by discussing its probability density function; and (ii) to specify the design requirements of a meteorological network, which will provide data for calculating the RDI and will be appropriate for the drought assessment of a region. Moreover, typical computational steps for precipitation network design are given and the underlying assumptions and limitations are briefly discussed.

Reconnaissance Drought Index (RDI)

The Reconnaissance Drought Index (RDI) (Tsakiris and Vangelis, 2005; Tsakiris *et al.*, 2007a) can be characterised as a general meteorological index for drought assessment. The RDI can be expressed with three forms: the initial value α_k, the normalised RDI (RDI_n) and the standardised RDI (RDI_{st}). In this paper we will focus on α_k and RDI_{st}.

The initial value (α_k) is presented in an aggregated form using a monthly time step and may be calculated on a monthly, seasonal or annual basis. The α_k for the year *i* and a time basis *k* (months) is calculated as:

$$\alpha_k^{(i)} = \frac{\sum_{j=1}^{k} P_{ij}}{\sum_{j=1}^{k} PET_{ij}}, \; i = 1 \text{ to } N \tag{1}$$

where P_{ij} and PET_{ij} are the precipitation and potential evapotranspiration of month *j* of year *i*, starting usually from October, which is customary for Mediterranean countries, and *N* is the total number of years of the available data.

The initial formulation of the RDI_{st} (Tsakiris and Vangelis, 2005) used the assumption that the α_k values follow the lognormal distribution and RDI_{st} is calculated as:

$$RDI_{st}^{(i)} = \frac{y^{(i)} - \bar{y}}{\hat{\sigma}_y} \tag{2}$$

in which y_i is the $ln(\alpha_k^{(i)})$, $\bar{y}$ is its arithmetic mean and $\hat{\sigma}_y$ is its standard deviation.

From an extended research on various data from several locations and different time scales (3, 6, 9 and 12 months) it was concluded that the α_k values follow satisfactorily both the lognormal and the gamma distributions in almost all locations and time scales, but in most of the cases the gamma distribution was more successful. Therefore, the calculation of the RDI_{st} could be performed better by fitting the gamma probability density function (pdf) to the given frequency distribution of the α_k, following the procedure described below. This approach also solves the problem of calculating the RDI_{st} for small time steps, such as monthly, which may include zero-precipitation values ($\alpha_k = 0$), for which Eq. (2) cannot be applied. The gamma distribution is defined by its frequency or probability density function:

$$g(x) = \frac{1}{\beta^{\gamma}\Gamma(\gamma)} x^{\gamma-1} e^{-x/\beta}, \quad \text{for } x > 0 \tag{3}$$

where γ and β are the shape and scale parameters respectively, *x* is the precipitation amount and $\Gamma(\gamma)$ is the gamma function. Parameters γ and β of the gamma pdf are estimated for each station and for each time scale of interest (1, 3, 6, 9, 12 months, etc.). Maximum likelihood estimations of γ and β are:

$$\gamma = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right), \; \beta = \frac{\bar{x}}{\gamma}, \quad \text{where} \quad A = ln(\bar{x}) - \frac{\sum ln(x)}{n} \tag{4}$$

and *n* is the number of observations.

The resulting parameters are then used to find the cumulative probability of α_k for a given year for the location in question. Since the gamma function is undefined for $x = 0$ and a precipitation distribution may contain zeros, the cumulative probability becomes:

$$H(x) = q + (1-q)G(x) \tag{5}$$

where *q* is the probability of zero precipitation and *G(x)* is the cumulative probability of the incomplete gamma function. If *m* is the number of zeros in an α_k time series, then *q* can be estimated by *m/n*. The cumulative probability *H(x)*, is then transformed to the standard normal random variable *z* with mean zero and variance of one (Abramowitz and Stegun, 1965), which is the value of the RDI_{st}.

The Standardised RDI behaves in a similar manner as the SPI (McKee *et al.*, 1993) and so do the results. Therefore, the RDI_{st} values can be compared to the same thresholds as the SPI. An example of annual values of SPI and RDI_{st} appears in Fig. 1, from Heraklion – Crete (Tsakiris *et al.*, 2007b).

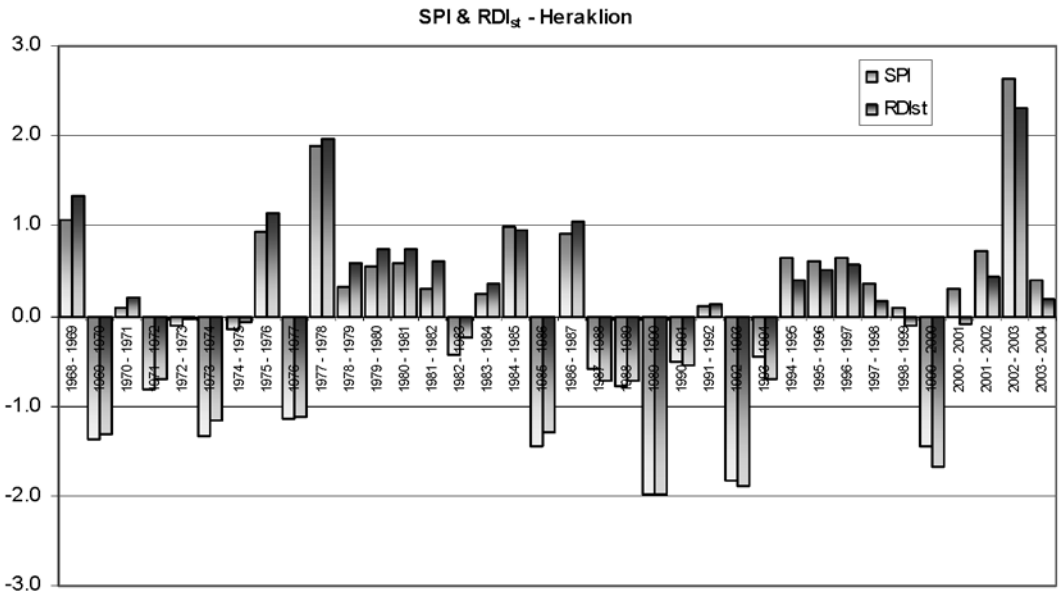

Fig. 1. Annual SPI and RDI_{st} values for hydrological years 1968/69-2003/04 for Heraklion – Crete.

In order to facilitate the calculation process of the RDI, a new software called DrinC (Drought Indices Calculator) was developed at the Laboratory of Reclamation Works & Water Resources Management of the National Technical University of Athens (Tsakiris *et al.*, 2007b). An online version of the software can be found at www.ewra.net/drinc.

Designing a drought monitoring network

In-depth study of drought indices shows that the main variables involved in drought assessment are: (i) precipitation in all its forms (rainfall, snowfall etc.); and (ii) potential evapotranspiration (PET). The second variable is assessed only indirectly through measuring other variables such as air temperature, air humidity, wind speed, surface roughness, etc. The latter is calculated through the Penman method or its extensions. In cases of lack of the necessary data, one could accept the Thornthwaite or the Hargreaves methods, which require only monthly air temperature data. The customary time scales are monthly, seasonal and annual. Consequently, processed aggregated data are expected to be used and in the worst case (with lack of data), the analyst will have to design a meteorological network for monthly precipitation and monthly air temperature.

Design of meteorological networks has long been a field of active research. It involves both technological and economic aspects. Traditionally, meteorological networks have been multi-purpose ones. Focusing on drought assessment implies the following constraints:

(i) Meteorological stations are selected from the existing meteorological network.

(ii) Drought assessment requirements cannot dictate the technical features of meteorological stations since these serve multiple purposes.

(iii) Optimisation of network design based on economic criteria is infeasible.

Since spatial variability of precipitation generally exceeds that of temperature, the key variable for network design is precipitation. This is the reason why our research has been restricted to the design of precipitation networks.

The critical point in designing precipitation network is choosing the spatial scale. Drought assessment is needed at spatial scales from a few km^2 to a few hundreds km^2. Hence, mean areal precipitation (MAP) at those scales is the key variable.

Naturally, the network design problem is reduced to an optimisation problem in which the net benefit NB is maximised. The NB is normally estimated from damage reduction due to drought assessment and the cost of network construction, operation and maintenance. The benefit and hence the net benefit are increasing functions of MAP accuracy. However, such optimisation is impossible since most networks are designed or operated as multi-purpose ones, which precludes direct relation between benefits and the MAP accuracy. The only criterion for network design remains that of keeping a minimum required MAP accuracy, which is assessed as the MSE of MAP. This requires two computational steps (Nalbantis *et al.*, 2006):

(i) Estimation of MAP accuracy of a trial network.

(ii) Definition of the MAP accuracy requirement by the user (in this case the analyst performing drought assessments).

The problem of estimating the MAP accuracy has been extensively studied in the last three decades of the past century. Well tested methodologies have been examined by Nalbantis *et al.* (2006). Methods with clear and reproducible analytical solutions were only selected. Literature was searched in a chronological order and methodological extensions were not considered as separate methodologies. Three methodologies meet these criteria:

Methodology A: researchers from the MIT, USA posed the problem of MAP estimation within a rigorous mathematical framework (Bras and Rodríguez-Iturbe, 1976).

Methodology B: researchers from the Institute of Hydrology, UK (Jones *et al.*, 1979) formulated a more application-oriented approach context which was applied with the aim to evaluate and restructure the whole precipitation network in the UK.

Methodology C: a research team from the National Polytechnic Institute at Grenoble, France (Lebel *et al.*, 1987) developed a methodology for network design which makes use of geostatistical tools such as kriging. The methodology has been validated based on data from an experimental basin in Southern France and a large-scale application within the global-scale experiment HAPEX-Sahel in West Africa (Lebel and Le Barbe, 1997).

After theoretical examination (Nalbantis *et al.*, 2006) Methodology C was selected for a number of reasons:

(i) It is based on the kriging method which is included in many general-purpose software packages.

(ii) It can exploit a wide variety of extensions of the kriging method.

(iii) Published results of its application exist for areas close to the Mediterranean.

(iv) No measurement errors are considered which is absolutely realistic for time scales used in this work.

(v) It has been more intensively applied to wide spectrum of spatial and temporal scales such as the domain of the HAPEX – Sahel experiment.

Typical methodological steps of Methodology C are (Nalbantis *et al.,* 2006):

(i) Estimating the empirical semi-variogram based on existing data.

(ii) Fitting a model to the empirical semi-variogram.

(iii) Selecting a sub-network as a candidate network.

(iv) Estimating of the MSE of MAP.

(v) Compare MSE to the desired accuracy; if this is not adequate return to step 3, else accept the network design.

As is known, the semi-variogram $\gamma(x_i - x_j)$ is defined as half the variance of the deviations of the studied field from one location x_i to another x_j. MAP is estimated as a linear function of point precipitations. The MSE of MAP is obtained analytically. In-depth explanation of the related equation is given by Nalbantis *et al.*, (2006).

The ratio of the semi-variogram of each realisation and the variance of the field is defined as the scaled semi-variogram. Averaging the scaled semi-variograms over the range of field realisations yields the scaled climatological semi-variogram (Lebel and Bastin, 1985). Applying kriging with the scaled climatological semi-variogram yields the scaled variance of MAP error which is the key criterion for network design since: (i) it depends on the average behaviour of the precipitation field in the area of interest; and (ii) it is linked to the configuration of the network only.

For testing a candidate network, the following typical computational steps are involved:

(i) Parameters of the kriging system equations are estimated for the scaled climatological semi-variogram.

(ii) The scaled variance of the MAP error is assessed.

(iii) The latter is multiplied by the field variance to yield the MSE of MAP.

Based on experience from applications of Methodology C in France and West Africa (Lebel and Le Barbe, 1997), the above typical computational steps were simplified into:

(i) Estimating the empirical semi-variogram based on data from an existing network.

(ii) Fitting an analytical model to the empirical semi-variogram and estimation of the decorrelation length which is equal to the range of the semi-variogram.

(iii) Selecting station sites for the candidate network.

(iv) Estimating the maximum inter-stations' spacing.

(v) If this is less than half the decorrelation length, then accept the network design, else return to step 3; this criterion has been verified by the French research team.

The methodology implies the assumptions of constancy of average point precipitation in space and the precipitation field isotropy. In geographical areas such as the Mediterranean these assumptions could be put in question due to the varied topography and the specific climatologic conditions. Suitable modifications of the above methodology are proposed by Nalbantis *et al.* (2006) and implemented by Nalbantis and Tsakiris (2006).

Concluding remarks

An attempt was made to specify the requirements of a drought monitoring network producing data for the calculation of the RDI. Since meteorological networks serve a variety of goals no benefit/cost optimisation was possible. Alternatively, a method based on geostatistical tools such as kriging was selected. Although some rather crude assumptions have been made for the precipitation field (e.g. spatial invariance of the mean and isotropy), the methodology was found to be adequate for assessing drought through the use of the RDI. In general terms, in areas where the assumptions hold, the desired spacing of the precipitation stations should be around 15 km. Since the target area is the Mediterranean with several anisotropies, it is deduced that further improvement of the methodology is needed, which is beyond the scope of this paper.

Acknowledgements

The major part of the paper is based on the research conducted within PRODIM project (INTERREG IIIB - ARCHIMED), funded jointly by EU and National funds.

References

Abramowitz, M. and Stegun, I.A. (1965). *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables*. National Bureau of Standards, Applied Mathematics Series – 55, Washington, DC.

Bras, R.L. and Rodriguez-Iturbe, I. (1976). Network design for the estimation of area mean of rainfall events. *Water Resour. Res.*, 12(6): 1185-95.

Jones, D.A., Gourney, R.J. and O'Connell, P.E. (1979). Network design using optimal estimation procedures. *Water Resour. Res.*, 15(6): 1801-1812.

Lebel, T. and Bastin, G. (1985). Variogram identification by the mean-square interpolation error method with application to hydrologic fields. *J. Hydrol.*, 77: 31-56.

Lebel, T., Bastin, G., Obled, C. and Creutin, J.D. (1987). On the accuracy of areal rainfall estimation: A case study. *Water Resour. Res.*, 23(11): 2123-2138.

Lebel, T. and Le Barbe, L. (1997). Rainfall monitoring during HAPEX-Sahel: 2. Point and areal estimation at the event and seasonal scales. *J. Hydrol.*, 188-189: 97-122.

McKee, T.B., Doeskin, N.J. and Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In: *Proceedings of the 8th Conference on Applied Climatology*, Anaheim, CA, 17-23, January, 1993. American Meteorological Society, Boston, MA, pp. 179-184.

Nalbantis, I. and Tsakiris, G. (2006). Case study: Selection of a drought monitoring network in Crete region. In: *Acquisition and Processing of Hydrometeorological Data for Drought Monitoring and Management*, Vol. I-Appendix, La Logia *et al.* (eds). Regione Siciliana, Palermo, Italy, pp. 1-6.

Nalbantis, I., Tsakiris, G., La Logia, G., Noto, L.V., Viola, F., Iiritano, G. and Caloiero, T. (2006). Meteorological monitoring networks. In: *Acquisition and Processing of Hydrometeorological Data for Drought Monitoring and Management*, Vol. I, La Logia *et al.* (eds). Regione Siciliana, Palermo, Italy, pp. 29-56 .

Tsakiris, G., Pangalou, D. and Vangelis, H. (2007a). Regional drought assessment based on the Reconnaissance Drought Index (RDI). *Water Resources Management*, 21: 821-833.

Tsakiris, G., Tigkas, D., Vangelis, H. and Pangalou, D. (2007b). Regional drought identification and assessment – Case study in Crete. In: *Methods and Tools for Drought Analysis and Management*, Rossi, G., Vega, T. and Bonaccorso, B. (eds). Springer, The Netherlands, pp. 169-191.

Tsakiris, G. and Vangelis, H. (2005). Establishing a Drought Index incorporating evapotranspiration. *European Water*, 9-10: 3-11.