MONITORING DROUGHT AT RIVER BASIN AND REGIONAL SCALE: APPLICATION IN SICILY

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MONITORING DROUGHT AT RIVER BASIN AND REGIONAL SCALE: APPLICATION IN SICILY

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Thousands have lived without love,

Not one without water

(W.H. Auden)

Laudato si', mi' Signore, per sor'aqua,

la quale è multo utile et humile

et pretiosa et casta.

(San Francesco d'Assisi)

Water is life's matter, matrix, mother, and medium.

There is no life without water.

(Albert Szent-Gyorgyi)

CONTENTS

ABSTRACT

The subject of the dissertation is the investigation of drought features, focusing especially to the characterization and monitoring of droughts at different spatial dimension.

Drought is a natural phenomenon, which presents spatial and temporal features whose knowledge is fundamental for a correct water resources management. Proper definition of droughts and quantification of its characteristics is essential for improving drought preparedness and for reducing its impacts.

Design of mitigation strategies to cope with drought is essential to alleviate many economic, social and environmental problems in different parts of the world and in Europe, particularly in the Mediterranean region (Iglesias et al., 2007; Rossi and Cancelliere, 2012).

Understanding space and time variability of droughts is fundamental for a wide range of water management problems. In order to achieve these goals, the need of appropriate indices oriented to support the analysis and monitoring of such extreme natural phenomenon throughout a multidimensional approach is required.

The multi facets nature of drought requires to assess the capabilities of monitoring indices to grasp different aspects related to the phenomenon. Also, the need arises to aggregate the information from different indices in order to simplify the assessment of drought conditions by decision makers, especially at river basin scale. On the other hand, at regional scale, assessment of the spatial features of drought in terms of areal extent is a prerequisite for a proper identification of appropriate mitigation strategies

The present thesis has addressed some of the above issue, attempting to contribute to a better drought monitoring at river basin and regional scale.

As first step, a methodology of analysis and comparison of most common drought indices has been applied. More specifically, a comparison between the Standardized Precipitation Index, the Standardized Streamflow Index, and the Palmer index has been carried out with reference to the Acate River watershed, in

the south of Sicily. Such comparison has revealed that the three indices present different degrees of agreement in detecting drought conditions depending on the adopted aggregation time scale. Furthermore the analysis has revealed that the SPI at a proper aggregation time scale can be representative of hydrological and agricultural droughts, thus confirming its suitability as a tool for monitoring droughts at river basin scale.

Then a methodology for the aggregation of such indices in a unique one based on Principal Component Analysis has been applied. The resulting index was able to clearly detect most of registered historical droughts; furthermore, the indirect presence of various components of the hydrologic cycle (precipitation, air temperature, streamflow) let the indicator have a lower sensitivity to the variability of a single hydrologic variable. The main advantage of the proposed aggregated index is that it integrates in a single value different information related to meteorological, hydrological, and agricultural droughts.

A methodology for the probabilistic characterization of drought areal extent based on SPI has been developed as a tool to support drought monitoring at regional scale. It consists in the estimation of the measure of drought severity associated with different areal extents (in terms of percentage area of the investigated region). Then a probability distribution has been fitted to drought severity series for different areal extents and drought Severity Area Frequency curves for the region of Sicily have been developed.

Comparison of the developed SAF curves with severity-area curves related to historical droughts, as well as to wet periods, has indicated the feasibility of the developed tool, both to characterize past droughts, as well as to probabilistically assess the magnitude of an ongoing drought for monitoring purposes.

CHAPTER 1

1 INTRODUCTION

1.1 Background

The latest World Water Development Reports (UN-Water, 2009, 2012) reminds the key role played by water for the whole economic system. Water is not just essential for human life, but also in achieving sustainable development objectives and therefore water availability can be one of the limiting factors for economic and social development. Droughts, being a temporary reduction of precipitation that propagates along the hydrological cycle causing severe water shortages, can therefore have catastrophic impacts especially in those regions already affected by water scarcity.

Europe and the entire Mediterranean area have suffered major droughts in recent years (Zaidman et al. 2001; Lloyd-Hughes and Saunders 2002; Fink et al. 2004; Hannaford et al. 2011; Bonaccorso et al., 2012). Other areas of the world are also experiencing drought conditions, such as continental USA and India, where the 2012 drought has been one of the worst in the last century.

Drought is a natural phenomenon, which presents spatial and temporal features whose knowledge is fundamental for a correct water resources management. Proper definition of droughts and quantification of its characteristics is essential for improving drought preparedness and for reducing its impacts. Furthermore, drought analysis and mitigation have gained further attention by the international scientific community also in light of new scenarios caused by potential trends in climate. It is expected that the intensity and frequency of droughts are going to increase in the future due to climate modifications with a considerable enhancement in inter-annual variability, associated with higher risks of heat waves and decreasing of precipitation, causing droughts as already experienced in recent years (IPCC, 2007).

Many authors have defined the drought concept (Yevjevich, 1967; Dracup et al., 1980; Yevjevich et al., 1983, Rossi et al. 1992; Wilhite, 2000); In general terms, a distinction is generally accepted among different drought related concepts:

- ✓ aridity indicates a natural and permanent climatic condition of low annual or seasonal rainfall;
- ✓ desertification identifies a permanent and often irreversible process of decrease or destruction of biological eco-system due to anthropic reasons or climate change effects;
- ✓ drought refers to a temporary natural condition of a consistent reduction of water availability with respect to long term average condition, spanning over a significant period of time and affecting a wide region.
- ✓ water shortage is a temporary deficit in the water balance between available resources and demand. It differs from water scarcity which is a permanent condition of insufficient water resources;

Further in this way, can be useful the following Table 1.I where is highlighted the distinction among water deficit phenomena based on their causes:

Table 1.I - Key elements for the definition of water scarcity and drought

		Timescale		
		Short-term (days, weeks)	Mid-term (weeks, months, seasons, years)	Long-term (decades)
Causes	Natural	Dry Spell	Drought	Aridity
	Anthropic	Water stress	Water scarcity	Desertification

Alternatively drought can be defined as an extreme hydro-meteorological phenomenon originated by meteorological anomalies that reduce precipitation thus affecting the state of the various components of the hydrologic cycle (Wilhite, 2000).

In spite of its basic nature of natural hazard, drought should also be considered a man-affected phenomenon (Rossi, 2000). Indeed, this is related to the perception of drought as a harmful phenomenon only where a human community exists and therefore its impacts can be very different according to the level of withdrawals with respect to the available water resources (Rossi et al., 2003). Furthermore, a drought of fixed duration and severity could produce a wide range of consequences according to the level of vulnerability of the water system (Cancelliere et al., 1998).

Design of mitigation strategies to cope with drought is essential to alleviate many economic, social and environmental problems in different parts of the world and in Europe, particularly in the Mediterranean region (Iglesias et al., 2007; Rossi and Cancelliere, 2012).

The ever-increasing demand on water resources calls for better management of the water deficit condition to avoid deficiency in the water supply systems. The consequences of droughts are felt most keenly in areas which are in any case arid (Beran and Rodier, 1985).

Understanding space and time variability of droughts is fundamental for a wide range of water management problems. In order to achieve these goals, the need of appropriate indices oriented to support the analysis and monitoring of such extreme natural phenomenon throughout a multidimensional approach is required.

The multi facets nature of drought requires to assess the capabilities of monitoring indices to grasp different aspects related to the phenomenon. Also, the need arises to aggregate the information from different indices in order to simplify the assessment of drought conditions by decision makers, especially at river basin scale. On the other hand, at regional scale, assessment of the spatial features of drought in terms of areal extent is a prerequisite for a proper identification of appropriate mitigation strategies.

1.2 Research objectives

It is largely recognized that an effective mitigation of the most adverse drought impacts is possible, as long as a drought monitoring is in place able to promptly warn about the onset drought and to follow its evolution in space and time (Rossi, 2003).

During last decades several methodologies for the identification and monitoring of drought events have been developed; more recently instead of the use of just one index, a set of different drought indices, synthesized in a few indicators, has been suggested (Keyantash and Dracup, 2004). Furthermore, the assessment of probabilities of areal extent of droughts at different severity levels over a large region can provide useful information to design drought management plans.

The overall objective of this study is to contribute to the development of appropriate methodologies for the assessment of drought occurrences in time and space to be adopted as monitoring tools for improved water resources planning and management. To this end, methods for drought identification and investigation of its intrinsic multidimensional characteristics are discussed and analyzed.

Specific objectives include:

- ✓ to analyze and compare some of the most widely used drought indices with specific reference to the river basin scale;
- ✓ to define an integrated drought index able to synthetically describe the condition of an area and/or a water supply system vulnerable to drought events;
- ✓ to develop a methodology to characterize probabilistically the relationship between drought severity and areal extent in a more significant regional scale.

CHAPTER 2

2 DROUGHT CHARACTERIZATION AND MONITORING

2.1 Definition of drought

The Glossary of Meteorology (1959) defines a drought as "a period of abnormally dry weather sufficiently prolonged for the lack of water to cause serious hydrological imbalance in the affected area. Drought is a relative word, therefore any discussion in terms of precipitation deficit must refer to the particular precipitation-related activity that is under discussion".

This means that whatever the definition, drought cannot be viewed solely as a physical phenomenon but it should be considered in relation to its impacts on society (Bordi and Sutera, 2001, Rossi 2003)

Deficit of precipitation, compared to "normal" amount, is the foremost reason of drought condition and it affects, directly or indirectly, all water balance parameters even if at different time scale.

Many classifications of drought from different perspectives exist (Yevjevich, 1967; Wilhite and M.H.Glantz, 1985; Tate and Gustard, 2000; Dracup et al., 1980). As drought propagates through the hydrological cycle, the different classes of drought are manifested (Figure 2.1)

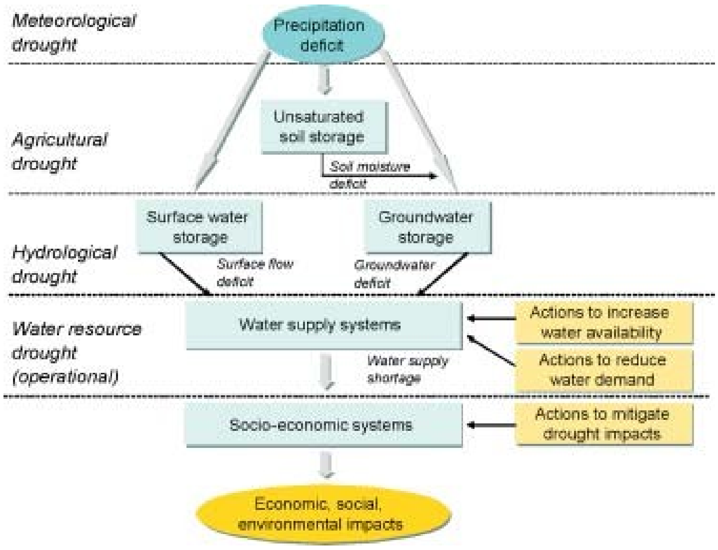

Figure 2.1 - Propagation of drought through the hydrological cycle (Rossi et al., 2007)

As shown in Figure 2.1, there is general agreement about defining four categories of drought: meteorological, agricultural, hydrological, and operational.

<u>Meteorological drought</u>. It refers to a precipitation deficit, with respect to a specified threshold, caused by variability of precipitation which is also linked to complex geophysical and oceanographic interactions; further, during latest years, meteorological droughts have been even more recurrent and, as stated by the IPCC (2007), "drought is likely to intensify in both duration and severity" due to climate change effects.

Consequences of meteorological drought are soil moisture deficit (agricultural drought) and low-flow conditions in surface and sub-surface water bodies (hydrologic drought).

<u>Agricultural drought.</u> It refers to a deficit of soil moisture caused by meteorological drought but with different timing and effects depending on initial moisture conditions and water storage capacity of the soil. This climatic excursion is sufficient to adversely affect cultivated vegetation and crop production.

<u>Hydrological drought.</u> Hydrological drought implies deficit of the "normal" water availability in rivers, lakes, groundwater level etc over large areas. It is characterized by low flows and low levels of surface water (rivers, lakes) and groundwater. In this research groundwater is not considered in detail for lack of

time series of observations. Hydrological droughts can have widespread impact by reducing or eliminating water supplies, deteriorating water quality, restricting water for irrigation and causing crop failure, reducing power generation, disturbing riparian habitats, limiting recreation activities (Mishra and Sing, 2008).

Operational drought. As a consequence of the natural phenomenon of drought, there are effects in the water supply system by means of water scarcity. It could be even defined as a socioeconomic drought because it associates the supply and demand of some economic good with elements of meteorological, hydrological, and agricultural drought. Socioeconomic drought occurs when the demand for an economic good exceeds supply as a result of a weather-related shortfall in water supply. A large body of theoretical and empirical literature has been developed that focuses on appropriate approaches for measuring direct economic impact of changes in water use levels and economic analysis of water resource developments to drought (Rogers et al., 1998).

2.2 Review of main drought indices

A thorough review of the literature was conducted to identify existing drought monitoring tools.

Drought indices are basically mathematic equations correlating main components of the hydrologic balance with some parameter characterizing droughts; most important parameters for drought classification are duration, severity, intensity, and areal extent. A drought index value is typically a single number, far more useful than raw data for decision making.

Operational definitions of drought typically require quantification of “normal" or “expected" conditions within specified regions; there are various methods and indices to analyze historical droughts or to monitor the evolution in space and time of current drought condition (Heim, 2000) and they measure different drought-causative and drought-responsive parameters, and identify and classify drought accordingly. Understanding what causes drought helps to predict it.

Usually two categories of drought indices are identified: “a priori” or “ex post” indices. The first type are forecasting indices, thus they indicate probabilities of drought occurrence (in a short time) through climate trend analysis. The “ex-post” indices are based on historical drought analysis and they could provide an evaluation of the ongoing climate condition.

The interdependence between climatic, hydrologic, geologic, geomorphic, ecological and societal variables makes it very difficult to adopt a definition that fully describes the drought phenomena and the respective impacts. A single definition of drought applicable to all spheres is difficult to formulate since concept, observational parameters and measurement procedures are different for experts of different fields. Beside, the concept of drought varies among regions of differing climates (Dracup et al., 1980). Consequently, a method to derive drought characteristics developed in one region is not necessarily appropriate or even applicable in another region. This is also the reason of numerous drought indices formulated: there is not a unique accepted definition and each drought index is generally based according to the scientific field of the author.

Since drought parameters are not linearly correlated with each other, correlation among various kinds of drought is also difficult. It is important to investigate the consistency of results obtained by different drought indices.

An accurate selection of indices for drought identification, providing a synthetic and objective description of drought conditions, represents a key point for the implementation of an efficient watch system.

Several drought indices have been proposed for drought monitoring, among which the Standardized Precipitation Index (SPI) (McKee et al. 1993), and the Palmer Index (Palmer, 1965), have probably found the most widespread application. Keyantash and Dracup (2004) proposed an aggregate Drought Index that considers all relevant variables of the hydrological cycle (precipitation, stream-flow, reservoir storage, evapotranspiration, soil moisture) through Principal Components Analysis in three different climatic divisions of California (U.S.A.). Estrela et al. (2006) use dimensionless indicators based on hydro-meteorological variables of water reserves with weights that are function of the percentage of the demand supplied by the considered specific resource in Jucar basin (Spain). Steinemann and Cavalcanti (2006) use the probabilities of different indicators of drought and shortage, selecting the trigger level on the basis of the most severe level of the indicator or the level of the majority of the indicators.

Whatever are the adopted aggregation criteria, the influence of possible no-stationarities on the hydrologic series, due also to climate changes, have to be taken into account for a better calibration of drought indices. (Cancelliere and Bonaccorso, 2004)

Water supply systems management under drought conditions should be based on information coming from a capable drought watching network. However not many research have been carried out for the integration of such information in management tools. Cancelliere et al (1998) relate information derived from monitoring system, such as drought severity identified by run methods and performance indices of supply systems; Kiem et al. (2004) evaluate the influence of climatic indices such an ENSO on the water supply systems management; Carbone et al. (2004) use joint probability of monthly mean temperatures and precipitations as support to definition of management rules of water supply systems.

A review of such drought indices has been provided by several authors as Yevjevich et al. (1978), Yevjevich et al. (1983), Beran and Rodier (1985), Rossi et al. (1992), and most recently, Tate and Gustard (2000), Heim (2000), Steinman et al. (2005) and Niemeyer (2008).

Depending on the typology of investigated drought it is possible to distinguish among meteorological, agricultural and hydrologic indices. Afterward are detailed characteristics of most widespread indices used to detect drought on its different aspects.

2.2.1 Meteorological drought indices

Standardized Precipitation Index

The Standardized Precipitation Index (SPI), developed by McKee et al. (1993), interprets observed rainfall as a standardized departure with respect to a rainfall probability distribution function.

The SPI index, being calculated on running cumulative values of precipitation at different range of time-step, permits to valuate anomalies in precipitation associated to several aggregation time scales: the choice of this scale have great influence on the different components of the hydrologic cycle that are taken into account.

Precipitation data are assumed to follow an incomplete gamma distribution (Redmond 2000). The original precipitation data are transformed to a normal distribution, which readily allows comparison between distinct locations and analytical computation of exceeding probabilities. Like rainfall deciles, the index requires a long span of precipitation observations; Guttman (1999) recommends at least 50 yr of data for drought periods of 1 yr or less, and more for multiyear droughts. The dimensionless SPI is computed as the discrete precipitation anomaly of the transformed data, divided by the standard deviation of the transformed data. The National Drought Mitigation Center (NDMC) computes the SPI with five running time intervals - 1, 3, 6, 9, and 12 months - but the index is flexible with respect to the period chosen.

Thus, the SPI can track drought on multiple timescales (Hayes et al. 1999). This powerful feature can provide an overwhelming amount of information unless researchers have a clear idea of the desired intervals.

The SPI thresholds ranges, defining seven possible climatic classes, are as follows (McKee et al., 1993):

Table 2.I – Climatic classification according to SPI

SPI	Rank
≥ 2.00	Extremely wet
da 1.5 a 1.99	Very wet
da 1.00 a 1.49	Moderately wet
da -0.99 a 0.99	Near normal
da -1.00 a 1.49	Moderately dry
da -1.50 a -1.99	Severely dry
≤ -2.00	Extremely dry

Computation method of SPI considers following steps:

- ✓ set of monthly precipitation data registered in selected rain stations and aggregation of such data to the desired aggregation time scale (e.g. 1,3,6,9,12, 18,24,36,48);
- ✓ calculation of parameters of the gamma probability function used to fit precipitation data; the probability density function (PDF) of gamma distribution is defined as:

$$f(x)=\frac{1}{\beta^{\alpha}\Gamma(\alpha)}x^{\alpha-1}e^{-x/\beta} \quad \text{per } x>0$$

where α and β are the shape and scale parameters respectively, x is the non-zero rainfall amount and $\Gamma(\alpha)$ is the gamma function.

$\Gamma(\alpha)=\int_0^{\infty} y^{\alpha-1}e^{-y}dy$ $\Gamma(\alpha)$ is the full gamma function

The maximum likelihood method is used to optimally estimate α and β parameters for each station, time scale and month of the year:

$$\alpha=\frac{1}{4A}\left(1+\sqrt{1+\frac{4A}{3}}\right)$$

$$\beta=\bar{x}/\alpha$$

Where $A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n}$ is the rainfall average, and n is the number of observations.

The cumulative probability for non-zero rainfalls, $F(x;\alpha,\beta)$ is then derived. The gamma function is undefined for x = 0 and data may contain zero rainfalls. Therefore, the cumulative probability $H(x)$ was calculated by the following equation:

$$H(x)=q+(1-q)F(x)$$

where q is the probability of a zero rainfall. If m is the number of zeros present in a rainfall time series, then q can be estimated by m/n. The cumulative probability is then transformed to the standard normal distribution so that the SPI mean and variance for the location and long-term record is zero and one respectively. SPI can be calculated for multiple monthly time scales (e.g., 3, 6, 12, 24, and 48 month time scales).

The cumulative probability H(x) is then transformed in the standardized variable Z with mean value 0 and variance 1, which correspond to SPI value. This equiprobability transformation is needed to have the same probability even in the normal distribution of the variable with a different distribution function.

The Z value of SPI could be obtained graphically comparing the cumulative probability distributions adopted or using a numerical approximation as suggested by Abramowitz e Stegun (1965), that transform the cumulative probability in to the standardized variable Z:

$$Z\text{=SPI=}-\left(t-\frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right) \quad \text{per } 0<H(x)\leq 0{,}5$$

$$Z\text{=SPI=}+\left(t-\frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right) \quad \text{per } 0{,}5<H(x)<1$$

where:

$$t=\sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \quad \text{per } 0<H(x)\leq 0{,}5$$

$$t=\sqrt{\ln\left(\frac{1}{(1-H(x))^2}\right)} \quad \text{per } 0{,}5<H(x)<1$$

Regardless of the apparent non-stationarity of some climatic processes, drought indices can be calibrated by assuming stationary series. Within this framework, Cancelliere and Bonaccorso (2004) have investigated the sampling properties of SPI, such as bias and mean square error (MSE), as a function of the sample size adopted for such distribution fitting, and computed the probabilities of correctly or incorrectly classifying drought conditions through the SPI. Wu et al. (2005) have analyzed the effect of the length of record on the SPI calculation by examining correlation coefficients, the index of agreement, and the consistency of dry/wet event categories between SPI values derived from different precipitation record lengths. The results show that SPI values computed from different lengths of records are highly correlated and consistent when the gamma distributions of precipitation over the different time periods are similar.

Hereinafter a drought period is assumed as a consecutive number of intervals where SPI values are at least in a moderate drought condition, namely less than -1. Then the following characteristics can be determined for each identified drought period:

- ✓ drought length (or duration) L defined as the number of consecutive intervals (months) where SPI remains below the threshold value -1;
- ✓ mean SPI value $\bar{Z}$ defined as the mean of SPI values within a drought period;
- ✓ minimum SPI value Z_{min} defined as the minimum SPI value within a drought period.

More precisely let Z_t indicate the SPI value at month t, for a given aggregation time scale of monthly precipitation. For each identified drought, drought length is given by:

$$L = t_f - t_i + 1$$

Where t_f and t_i are such that:

$$Z_t < -1 \; for \; t_i \le t \le t_f \text{ and } Z_t > -1 \; for \; t = t_{i-1} \; and \; t = t_{f+1}$$

The mean SPI value can be expressed as:

$$\bar{Z} = \frac{1}{L} \sum_{t=t_i}^{t_f} Z_t$$

The minimum SPI value is given by

$$Z_{min} = \min(Z_{t_i} \ldots \ldots, Z_{t_f})$$

Palmer Drought Severity Index (PDSI) and Moisture Anomaly Index(Z)

The most prominent index of meteorological droughts is the Palmer Drought Severity Index (PDSI). The PDSI and the Z-index were both developed by Palmer (1965) and have been widely used in the scientific literature (Alley, 1984; Karl *et al.*, 1986). The PDSI was created with the intent of "measuring the cumulative departure of moisture supply" (Palmer 1965).

The Palmer index is based on hydrological balance of soil and takes in account precipitation as well as evapotraspiration assuming as drought indicator the anomalies between the effective precipitation and the "climatically appropriated".

In its original code arrangement, allows just analysis of historical droughts, thus a modified version, called PHDI (Palmer Hydrological Drought Index), has been applied by several public authorities in the USA to monitor drought condition, in order to implement a check and planning system in agriculture production.

The PDSI calculates a series of water balance terms for a generic two-layer soil model, and fluctuations in the hypothetical moisture supply, depending upon observed meteorological conditions, are compared to a reference set of water balance terms. This comparison leads to computation of the dimensionless PDSI.

Computation of the PDSI is complicated; for an in-depth discussion of the numerical steps, see Alley (1984). The PDSI is ideally a standardized measure of moisture conditions across regions and time. The shortcomings of regional comparability, which the PDSI was designed to facilitate, are further detailed by Guttman (1991). The PDSI is also imprecise in its treatment of all precipitation as rainfall, as snowfall may not be immediately available as water in the two-layer soil scheme.

The PDSI and Z-index are derived using a soil moisture/water balance algorithm that requires a time series of daily air temperature and precipitation data, and information on the available water content (AWC) of the soil. Soil moisture storage is handled by dividing the soil into two layers. The top layer has a field capacity of 25 mm, moisture is not transferred to the second layer until the top layer is saturated, and runoff does not occur until both soil layers are saturated. Applying the two-layer water budget model proposed by Palmer (1965):

$$AWC\ (mm) = AWC_s + AWC_u$$

where *AWCs* is referred to the superficial layer of the soil that can be assumed to be constant and equal to 25,4 mm while *AWCu* is referred to the underlying soil structure and depends on soil characteristics and thickness of root system.

Potential evapotranspiration (PE) is calculated using the Thornthwaite (1955) method condensed in the formula:

$$PE_{ij} = 16d_j \left(\frac{10\, T_{ij}}{TE_i}\right)^{ai}$$

and water is extracted from the soil by evapotranspiration when PE > P (where P is the precipitation for the month). Evapotranspiration loss from the surface layer of the soil (L_s) always is assumed to take place at the potential rate. It is also assumed that the evapotranspiration loss from the underlying layer of the soil (L_u) depends on the initial moisture conditions in this layer, PE, and the combined available water content in both layers.

The Z-index is a measure of the monthly moisture anomaly and it reflects the departure of moisture conditions in a particular month from normal (or climatically appropriate) moisture conditions (Heim, 2002). The first step in calculating the monthly moisture status (Z-index) is to determine the expected evapotranspiration, runoff, soil moisture loss, and recharge rates based on at least a 30-year time series. A water balance equation is subsequently applied to derive the expected or normal precipitation. The monthly departure from normal moisture, d, is determined by comparing the expected precipitation to the actual precipitation. The Z-index, Z_i, then is the product of d and a weighting factor K for the month i,

$$Z_i = d_i K_i$$

where K_i is a weighting factor that is initially determined using an empirically derived coefficient, K', and then adjusted by a regional correction factor that is used to account for the variation between locations. Monthly values of K_i are calculated using

$$K_i = \left(\frac{17.67}{\sum D_i K_i}\right) * K'$$

where D is obtained during the calibration period by determining the mean of the absolute values of d for each month of the year.

The PDSI, indicated by X_i, is a combination of Z_i, for the current month, and the PDSI value for the previous month,

$$X_i = \left(\frac{Z_i}{3}\right) + 0.897\, X_{i-1}$$

While both the Z-index and the PDSI are derived using the same data, their monthly values are quite different. The Z-index is not affected by moisture conditions in the previous month, so Z-index values can vary dramatically from month to month. On the other hand, the PDSI varies more slowly because antecedent conditions account for two-thirds of its value. Although the PDSI was designed to measure meteorological drought, it may be more appropriate as a measure of hydrological drought and, according to Karl (1986), the Z-index may be a better measure of meteorological or agricultural drought. It should be noted that although both the Z-index and PDSI are strongly weighted by both precipitation and temperature anomalies, most other meteorological indices (e.g., SPI, EDI, percent normal, deciles) are calculated using only precipitation. Alley (1984), Karl (1986), and Guttman (1998) have completed detailed evaluations of the limitations of the PDSI and Z-index, their work, along with the work of other researchers, has been summarized by Heim (2002). On the positive side, the PDSI does factor in antecedent conditions and is calculable from basic data. But its empirical nature, coupled with the fact it was developed for U.S. agricultural regions, limits its broad applicability, and as a result the PDSI is not used internationally. (Gibbs and Maher, 1967), Hayes (2000) considered its application for Australia but instead recommended rainfall deciles.

Cancelliere et al. (1996) verified the applicability of Palmer index in the Mediterranean area, selecting some basin located in Sicily, Greece and Cyprus. Comparison among PHDI and rolling mean values of some hydrologic variables, for different periods, shows a good correspondence of relative results.

The PDSI is a dimensionless number typically ranging between 4 and −4, with negative quantities indicating a shortage of water as shown in table 2.II.

Table 2.II – Climatic classification according to Palmer Index

PDSI	Rank	PDSI	Rank
≥ 4.00	Extremely wet	from-0.50 to -.99	Incipient drought
From 3.00 to 3.99	Very wet	from -1.00 to -1.99	Mild drought
From 2.00 to 2.99	Moderately wet	from -2.00 to -2.99	Moderate drought
from 1.00 to 1.99	Slightly wet	from -3.00 to -3.99	Severe drought
from 0.50 to .99	Incipient wet spell	≤ -4.00	Extreme drought
from 0.49 to -.49	Near normal		

2.2.2 Hydrological drought indices

Hydrological droughts are associated with the impact of prolonged precipitation deficiencies on water supply from surface or subsurface sources such as rivers, reservoirs and groundwater (Keyantash and Dracup, 2002). Similarly, the American Meteorological Society defines hydrological drought as "*Prolonged period of below-normal precipitation, causing deficiencies in water supply, as measured by below-normal streamflow, lake and reservoir levels, groundwater* *levels, and depleted soil moisture content*". The drought indices reviewed in this section can be used to represent hydrological droughts.

There is an inherent time-lag between meteorological drought and hydrological drought because it takes longer for the precipitation deficiency to be reflected in streamflow and reservoir levels. This is especially important in places where groundwater is a major contributor to the streamflow and reservoirs. After a hydrological drought becomes established, even if the precipitation level returns to normal, it takes time for the hydrological drought to end. The time-lag will be small in areas with high precipitation and small reservoirs, because storm flows usually fill up the reservoirs to pre-drought levels. The time-lag will be large in areas of low precipitation and where spring discharge (from snowmelt) accounts for a significant amount of the total annual flow.

Drought indices such as Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982) and Palmer Hydrological Drought Index (PHDI) (Karl, 1986) are commonly used to monitor hydrological drought. Further are also considered other indices like the Standardized Streamflow Index (SSI), Streamflow Deficit Index (SDI), Standardized Reservoir Index (SRI), and the Reservoir Deficit Index (RDI). These four indices are based directly on the reservoir and streamflow data, but these indices use a different standardizing procedure.

Standardized Stream-flow Index

The Standardized Streamflow Index (SSI), specifically developed for this study demonstrates great promise for monitoring hydrological drought. SSI is a standardized measure of streamflow that is similar in formulation to the SPI. McKee *et al.* (1993) developed a standardizing procedure for evaluating precipitation departures (e.g., SPI) using a probability distribution function. A similar approach was used to develop the Standardized Streamflow Index (SSI).

The computation on a monthly time step of SSI consists of following steps:

- ✓ Compute rolling cumulative monthly stream flow for several aggregation time scales for the range of years based period of record;
- ✓ For each time scale, for each month of the year, fit a transformation to convert the data into some probability function distribution: for the sake of consistency we assumed that the transformed data fit the normal distribution function;
- ✓ Compute the mean and standard deviation of the transformed data;
- ✓ Compute the Z values in a standard normal distribution (i.e., Z = (X – Mean)/Standard Deviation), which is SSI.

SSI is very similar to the standardized and deseasonalized stream-flow aggregated at correspondent time scale. The standard stream of 30-day mean flow would be equivalent to the SSI-k1 calculated using 30-day cumulative stream flow.

Surface water supply index (SWSI)

The Surface Water Supply Index (SWSI) is a hydrological drought index that was developed by Shafer and Dezman (1982) as an indicator of surface water conditions in order to replace the PDSI in areas where local precipitation is not the sole (or primary) source of streamflow (Shafer and Dezman, 1982). SWSI was designed for mountainous locations with significant snowfall because of the delayed contribution of snowmelt runoff to surface water supplies. The SWSI is calculated based on the monthly non-exceedance probability which is determined using available historical records of reservoir storage, streamflow, precipitation, and snowpack. Using a basin-calibrated SWSI algorithm, weights are assigned to each hydrological component based on its typical contribution to the water supply Then SWSI is calculated as a sum of the products of the probability of each the hydrological components and their respective weights.

It considers rainfall, streamflow/snow water content, and reservoir storage volume in formulating SWSI.

The mathematical formulation of the SWSI is as follows:

$$SWSI = \frac{\left[(a * PN_m) + \left(b * PN_{fs/fn}\right) + (c * PN_{rs}) - 50\right]}{50}$$

where, PN is the probability of non-exceedance (%); rn, sf, sn, and rs is refer to rainfall, streamflow, snow water content and reservoir storage volume components respectively; a, b, c are weights for each component and must meet the condition $a+b+c = 1$. Subtracting 50 and dividing by 12 are a centering and compressing procedure designed to make the index value have a similar magnitude to the PDSI (Palmer, 1965).

Because it is dependent on the season, the SWSI is calculated using only reservoir storage, snowpack, and precipitation during the winter (December through May). During the rest of the year (June to November) streamflow replaces snowpack in the SWSI equation. Calculations are performed on a monthly time step. Monthly data are collected and summed for all locations where reservoir storage, streamflow, precipitation, and snowpack are measured in the basin.

Each component is normalized using the historical data. The probability of non-exceedance (e.g., the probability that subsequent values of that component will not exceed the current value) is determined for each component using frequency analysis. Converting all of the components to a non-exceedance probability allows their values to be compared to each other. The SWSI, similar to PDSI, has an arbitrary scale that is centered on zero and ranges from –4 to +4 as follows (Shafer and Dezman, 1982): 4.0+, abundant supply; 2.0+, Near normal; -1.0, incipient drought; -2.0, moderate drought; -3.0, severe drought; and -4.0, extremely drought.

SWSI is a particularly good measure of surface water supply conditions because it accounts for the major hydrological variables that contribute to surface water supply there.

2.2.3 Agricultural drought indices

Crop moisture index

Palmer (1968) developed the Crop Moisture Index (CMI) to monitor short-term changes in moisture conditions affecting crops. The CMI is the sum of an evapotranspiration deficit (with respect to normal conditions) and soil water recharge. These terms are computed on a weekly basis using PDSI parameters, which consider the mean temperature, total precipitation, and soil moisture conditions from the previous week (Palmer 1968).

The CMI can assess present conditions for crops, but it can rapidly vacillate and is a poor tool for monitoring long-term drought (Hayes 2000). For example, a rainstorm may briefly bring crops adequate moisture, even though an extended drought persists. The CMI also begins and ends each growing season near zero, which may be appropriate for botanical annuals, but not for tracking long-term drought. As a consequence, the assessment of agricultural drought is better suited to the related Palmer Z index (Karl 1986).

2.2.4 Operational indices

Multivariate Aggregate Drought Index

The Aggregated Drought Index (ADI) is a multivariate index developed by Keyantash and Dracup (2004) which derives a single value using Principle Component Analysis (PCA) over data from hydrological, meteorological, and agricultural drought regimes. The ADI is designed for use over regions of climatic uniformity, such as climate divisions defined by the Nation Climatic Data Center (NCDC) (Keyantash and Dracup, 2004). Its input variables represent the fluctuations in water volume within the hydrologic cycle; ADI incorporates several variables that define the hydrologic cycle and any combination of six parameters describing bulk water content within a climate division: Precipitation (P), Evapotranspiration (E), Streamflow (Q), Reservoir Storage (V), Soil Moisture Content (W), and Snow Water Content (s). The ADI is flexible such that the entire suite of parameters or just selected variables can be used over each time step, since each time step is treated independently. Keyantash and Dracup, 2004 were able to correlate the ADI with severe droughts in three California climate divisions.

The Principal Component Analysis (PCA) was used to aggregate the aforementioned variables. Computation of the Principal Components (PCs) requires constructing a square (p x p, where p is the number of variables) symmetric correlation matrix to describe the correlations between the original data.

The PCs are a re-expression of the original p-variable data set in terms of uncorrelated components Z_j ($1 < j \leq p$). Eigenvectors derived through PCA are unit vectors (i.e., magnitude of 1) that establish the relationship between the PCs and the original data:

$$Z = XE$$

where, Z is the n x p matrix of PCs (i.e. uncorrelated components); in which n is the number of observations, X is the n x p matrix of standardized observational data, and E is the p x p matrix of eigenvectors.

As was done by Keyantash and Dracup (2004), the ADI was considered as the first PC (PC1), normalized by its standard deviation:

$$ADI_{i,k} = \frac{Z_{i,k}}{\sigma_k}$$

where, $ADI_{i,k}$ is the ADI value for month k in year i, $Z_{i,k}$ is the first PC during year i for month k, and σ is the sample standard deviation of $Z_{i,k}$ overall years for month k.

The ADI utilizes only the PC1 because it explains the largest fraction of the variance described by the full p-member standardized data set.

2.3 Calculation of indices and drought classification

Drought events are selected from the indices time series using the threshold level method (e.g. Yevjevich, 1967), which defines the drought as a period when the variable analyzed is below a certain threshold value (i.e. in a deficit situation). At each time step the start and end of the drought is identified. The following characteristics are derived for each event:

- ✓ drought duration
- ✓ average deficit volume
- ✓ drought magnitude

As defined by Yevjevich (1967), the duration L_d of a drought event j is assumed as the number of uninterrupted time steps (in the present study: months) with a state variable below the threshold for one or more time steps:

$$L_d = t_f - t_i$$

The average deficit volume of a drought event j over the catchment area is defined as the sum of the deficit volumes over an uninterrupted number of months with the state variable below the classification threshold for one or more time steps:

$$D_c = \sum_{t=1}^{L_d} (x_0 - X_t)$$

where D_c is the deficit volume.

While the drought magnitude is given by the ratio between cumulative deficit and duration:

$$I = \frac{D_c}{L_d}$$

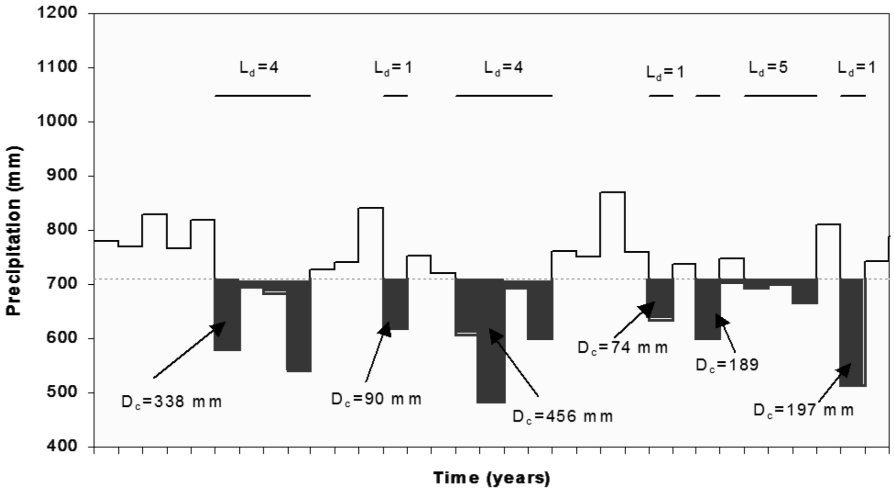

Figure 2.2 – Identification of duration and deficit of an hydrologic variable with the threshold level methods (Yevjevich, 1967)

To detect drought events, adopted thresholds were the numerical limits of drought classification proposed by respective authors of indices (reminded above) and applied to correspondent time series. An indicator function is introduced, which specifies that a drought occurs, if true (=1, below the threshold) and a non-drought condition occurs, if false (=0, above the threshold).

2.4 Criticism of existent drought indices

The first step in determining which meteorological and hydrological drought indices are the most appropriate for monitoring drought conditions at the local level was to review the scientific literature and compile a list of the strengths and weaknesses of each index. In this section the data requirements of each drought index will also be described since the purpose of this study is to identify drought indices that can be calculated operationally. Therefore the "best" drought indices are those that can be calculated using readily available data. Only those indices that are critiqued in the literature have been included in this section.

The PDSI, PHDI, and Z-index are all calculated using the algorithm that was developed by Palmer (1965) and therefore, for simplicity, all of the discussion will use the term PDSI to refer to all three of these indices.

The PDSI is calculated using temperature and precipitation data. The daily temperature and precipitation data are aggregated to weeks or months, depending on the time-scale of interest. The PDSI also needs information on the available water holding capacity of the soil. Since the PDSI uses the Thornthwaite (1948) method for estimating PET, the latitude of the location also needs to be provided.

The PDSI was the first comprehensive drought index developed in the U.S. and it is widely used for drought monitoring and within state drought plans (Heim, 2002). Despite its widespread use, the PDSI has many limitations. One of the limitations of the PDSI is that PET is estimated using Thornthwaite's method (which only considers monthly temperatures to estimate PET) (Narasimhan and Srinivasan, 2005). More realistic estimates of PET can be generated by using a physically-based method such as the FAO Penman-Montieth equation (Allen *et al.*, 1998). However a recent study determined that calculating the PDSI with a more physically-based method of calculating ET did not improve the correlation between the PDSI and soil moisture at the study sites (in Greece).

Another limitation of the PDSI is that it uses a two layer soil model with just a single parameter for the available water holding capacity of the soil. This may be reasonable when calculating the PDSI for a single location (e.g., station), but it is inappropriate for calculating the PDSI for regions, such as climate divisions within which the soil is highly spatially heterogeneous (Narasimhan and Srinivasan, 2005). There is no way to represent the horizontal and vertical heterogeneity of soil properties in the PDSI water balance. It is important to use an appropriate value for the available water holding capacity of the soil because it has been demonstrated that the PDSI is sensitive to changes in this parameter (Karl, 1986).

The PDSI also assumes that runoff only occurs when the two soil layers are both completely saturated. In reality runoff varies due to differences in slope, soil type, land use, land cover, and land management practices (Narasimhan and Srinivasan, 2005). None of these factors are accounted for in the PDSI. Alley (1984) noted that there are also problems with how runoff is generated because the model does not account for the distribution (or intensity) of precipitation within the week or month. The PDSI also does not account for the seasonal changes in vegetation growth and root development and it is not designed to deal with a snowpack or frozen soil (Alley, 1984; Karl, 1986; Karl *et al.*, 1987).

PDSI is highly dependent on the weighting factor used to make it comparable between different regions (and months) (Heim, 2002). Palmer (1965) calculated the regional correction factor (K) based on data from only nine locations in seven states and calculated the duration factors 0.897 and 1/3 based on data from western Kansas and central Iowa and they affect the sensitivity of the index to precipitation events (Wells *et al.*, 2004). An improvement proposed by Wells *et al.* (2004) is meant to correct the lack of spatial comparability by dynamically calculating the regional correction factor (K) and the duration factors using historical climate data from each location.

The original formulation of the PDSI is known to be spatially and temporally variants and therefore it cannot be compared across different countries or between months (Alley, 1984; Guttman *et al.*, 1992; Guttman, 1998; Heim, 2002). This means that severe and extreme droughts as defined by the PDSI occur more often in some parts of the country than others (Wells *et al.*, 2004).

The length of the calibration period (historical record) will have an influence on the stability of the estimated parameters. Longer calibration periods tend to provide more consistent PDSI values (Karl, 1986). For comparison purposes, the same calibration period should be used for all locations. Interpreting the PDSI can also be a challenge since it is a function of both temperature and precipitation data. It has been demonstrated that the PDSI responds in a non-linear fashion to changes in precipitation.

Although the PDSI is often defined as a meteorological drought index the PDSI responds rather slowly to changes in moisture conditions. According to Guttman (1998), the PDSI has a ‘memory’ (its spectrum conforms to that of an autoregressive process) and it is highly correlated with the 12-month SPI (Heim, 2002). This means that both the PDSI and PHDI are more appropriate for measuring hydrological droughts. The Z-index can be used for measuring agricultural and meteorological drought since it only accounts for the moisture conditions during the current week or month.

The drought classification that was proposed by Palmer (1965) was arbitrarily determined, so those thresholds are not appropriate for making water management decisions or triggering drought response programs or declarations of drought emergency unless they have been confirmed by an independent local assessment (Alley, 1984). It has also been demonstrated that the calculation procedure for transitioning between wet and dry spells tends to produce an asymmetrical and bimodal distribution of PDSI values (Alley, 1984; Heim, 2002). Therefore, the PDSI is not normally distributed and cannot be interpreted in the same way as other indices, such as the SPI.

Speaking on which, SPI is a popular drought index because of its simplicity and versatility. To calculate the SPI one only needs weekly or monthly precipitation data (depending on the time scale on the intended application). The SPI can be calculated for any time period of interest.

Time-scales are appropriate for monitoring different types of drought and correspond to different drought impacts. Unlike the PDSI, the SPI is spatially invariant (Guttman, 1998; Heim, 2002; Wu *et al.*, 2007) and so values of the SPI can readily be compared across time and space. Although the SPI can be calculated in all climatic regions (Heim, 2002), it is important to note that arid regions, those that experience many months with zero precipitation, may be problematic for the SPI depending on which PDF is used to normalize precipitation (Wu *et al.*, 2005). The SPI is also easier to understand and interpret than the PDSI since its value is only based on precipitation and since it is reported in standard deviations away from the mean.

However, there are some limitations associated with the SPI. Like the PDSI, it is computationally complex (it cannot be calculated by hand or with a spreadsheet) and it requires specialized code. The SPI also requires a long (and complete) precipitation record.

It has been demonstrated that the SPI is strongly influenced by record length (Wu *et al.*, 2005). Therefore when comparing stations to each other, it is best if they have the same length of precipitation record. The minimum precipitation record for calculating the SPI is 30 years, but it is recommended to use 50+ years of data (and the extreme values of the SPI may only be accurate when even longer precipitation records are used (80+ years)) (Wu *et al.*, 2005).

It can also be demonstrated that the SPI will be strongly influenced by the presence of missing data (and the interpolation/replacement of missing data). This analysis demonstrates that decisions that are made about how missing data is handled will have a direct impact on the magnitude of precipitation-based drought indices such as the SPI.

The SPI is also influenced by normalization procedure (e.g., PDF selection) that is used. Guttman (1999) analyzed six different PDFs (including: the two-parameter gamma; the two-parameter gamma, for which the parameters are estimated by the maximum likelihood method; the three-parameter Pearson Type III; the three-parameter generalized extreme value; the four-parameter kappa; and the five-parameter Wakeby) and determined that the Pearson Type III was the most appropriate PDF for calculating SPI. Using a different PDF will generate different SPI values.

Vicente-Serrano and Begueria (2003) point out that drought indices are not as useful in identifying spatial patterns of drought risk since they are based on standardized or normalized shortages in relation to "average conditions", which relate to a given station and a given period. This holds true for both the SPI and the PDSI indices. As a result, the frequency of drought spells is about the same for all stations no matter if they lie in extremely arid or extremely rainy regions, even though the rainy sites may receive several times more rain than the arid sites. Similarly, these indices cannot be used in climate-change impact assessments, as they would provide approximately the same distributions for both present and changed climates regardless of the changes in the climatic conditions.

Regarding the Standardized Streamflow Index, one of the main advantages is that it can be calculated for a wide range of time scales and, using daily data, it can be updated on a daily rather than monthly basis. Therefore it can be used to monitor short, medium, or long-term hydrological drought in near-real time. The index is a standardized measure of streamflow based on a statistical measure and so it is more robust that just using streamflow departures. Interpretation of SSI is straightforward, negative values indicate below normal streamflow and positive values indicate above normal streamflow. Since the index is standardized, it can be compared across space and time.

One of the main weaknesses of the SSI is that it is very difficult to fit a statistical distribution to the raw cumulative streamflow data (Serrano et al. 2012), hence the data has to be transformed and. even after being transformed, especially during low-flow periods and for short-accumulation time scales, the data did not fit a normal distribution. This could potentially introduce errors in the calculation of the index. Also it is difficult to find gage records that are appropriate for calculating the SSI since there are a limited number of long streamflow records for gages unaffected by upstream reservoirs.

2.5 *About areal extent of drought*

Although the estimation of drought severity and duration at watershed scale gives useful information for water management, it is interesting and important to assess drought over a wider region by considering also the areal extension of the drought.

The regional analysis consents to determinate general characteristics and spatial distribution of droughts, as well as an evaluation of the most affected areas where socio-economic and environmental impacts are relevant: a more exhaustive awareness of these natural extreme events is indispensable for adequate planning and implementation of effective mitigation measures.

To reach this purpose Yevjevich, in 1967 proposed the method of run to detect at-site droughts; effectively it can be extended in the analysis of regional droughts by considering time series of the variable used as parameter of the study and for which are available measurements registered at several stations and selecting, besides the truncation level at each site, an additional threshold, which represents the value of the area affected by deficit above which a regional drought is considered to occur (Santos, 1983).

The statistical properties of such detected droughts can be then investigated; for example Rossi (1983) analyzed the historical series of areal coverage and regional deficit in order to verify whether the two characteristics differ significantly over different basin to assess the possibility of adopting an interbasin water transfer as a drought mitigation measure.

Alternatively, characteristics of drought indices could be investigated by means of statistical tools in order to obtain the probability distribution function of the indices. Further, the Monte Carlo method can be applied simulating the characteristics of drought indices over a large region, as in the study of Tase (1976) and Tase and Yevjevich (1978).

Several methods can be adopted to describe historical regional drought events requires, through the investigation of the spatial variability of the underlying variable or, as an alternative, of a drought index. One of the commonly adopted method for analyzing spatial variability of drought events is by drawing isoline maps of a drought descriptor, such as:

- ✓ the rainfall depth at the time interval i, expressed as a percentage of the corresponding long term mean;
- ✓ the deviation of the total rainfall computed on a past drought period from the corresponding long term mean, namely the rainfall deficit, expressed as absolute value or ratio or percentage of the mean;

- ✓ the standardized deficit obtained as the ratio, for a given time interval, of the rainfall deviation from the mean over the standard deviation.

Also, the areal extent of an historical drought can be drawn by plotting a drought descriptor versus the corresponding percentage areal coverage.

Alternatively, the relationship between a drought descriptor of selected probability of occurrence and the corresponding percentage areal coverage can be adopted to analyze spatial variability of droughts. Among the latter category, drought severity-area-frequency (SAF) curves have been proposed for assessing drought in a region.

One of the first works on SAF curves has been carried out by Rossi (1983). In this study, curves relating the areal weighted (by means of Thiessen polygons) precipitation deficits of fixed return period to the corresponding areal coverage are derived with reference to different aggregation time periods for Sicily region, Italy.

The approach generally adopted to derive SAF curves consists of the following steps (Kim et al., 2002; Loukas and Vasiliades, 2004;Mishra and Desai, 2005;Mishra and Singh, 2008):

- ✓ identify the variable at a suitable time scale (e.g. monthly precipitation) to be used for estimating drought characteristics;
- ✓ spatially interpolate local values on a fixed point grid;
- ✓ identify drought and drought characteristics (e.g. by applying the theory of runs or by computing one or more drought indices for each gridded time series);
- ✓ estimate a measure of drought severity (e.g. sum of negative runs in a dry spell, sum of negative SPI values in a dry spell, etc.) associated with different areal extents (in terms of percentage area) by considering different areal threshold;
- ✓ determine the best probability distribution fitting drought severity series for different areal extents;
- ✓ perform frequency analysis in order to associate drought severity with different return periods;
- ✓ construct SAF curves for the region under consideration.

CHAPTER 3

3 METHODOLOGIES OF DROUGHT ANALYSIS AT DIFFERENT SPATIAL SCALES

3.1 Introduction

In previous chapter some of the most common indices generally adopted to characterize and monitor drought events have been presented, also with reference to the required data and calculation procedures.

In this part of the thesis methodologies presented in the research are discussed. Substantially the chapter is addressed in three main arguments:

- ✓ In the first part are presented methodologies to compare results coming from drought analysis carried out implementing most common drought indices;
- ✓ In the second part a method of aggregation of those drought indices into a unique indicator is illustrated;
- ✓ In the third part a methodology to explore the severity of drought areal extent and to characterize probabilistically his frequency is discussed.

In order to achieve the objectives of the research three of the presented indices have been selected to carry on the drought analysis: the Standardized Precipitation Index, the Standardized Streamflow Index and the Palmer Hydrologic Drought Index. Furthermore, they have been functional to the local drought analysis, while the SPI has been selected as drought variable to achieve the probabilistic regional investigation.

3.2 Comparing methods of identified droughts

3.2.1 Overview

In order to evaluate characteristics of identified drought events, understanding of information derived from drought indices is essential as well as the choice of the best comparing methodology.

Nevertheless, due to considerable differences among indices in terms of its formulation hypothesis, variables involved and aggregation time scale it is reasonable to attend that indices do not detect droughts having identical characteristics. Thus, the comparison is useful for a deeper analysis of indices and its understanding and applicability in different environmental and climatic condition.

Essentially two types of comparison analyses could be adopted:

- ✓ qualitative analysis based on observation of graphs, tables, etc.;
- ✓ quantitative analysis based on application of correlation analysis, concordance matrices, spectrum analysis, etc..

Considering a fixed time period for which are available time series of the hydro-meteorological parameters involved on indices calculation, once calculated index values per each time step, it is appropriate to establish some evaluation criteria as suggested in following points:

- ✓ it is convenient to compare values of drought index at each time step of the fixed time period;
- ✓ evaluation of drought classification assigned by indices at each time step;
- ✓ comparison of parameters characterizing identified drought events.

The first two criteria allow a concordance evaluation in classifying just each time step, without any overview about characteristics of the whole drought period. In particular the first point alludes to a straight comparison of calculated indices values related to the same interval and can be helpful in case indices are continuous variables. The second criterion assumes that a standard classification of drought is already settled for each index and it focuses to compare the assigned classification. The third comparison refers on ability of indices on detecting and characterizing a drought event and it depends on definition of starting and conclusion of a drought interval.

To investigate even the spread of the drought event over a region, analysis of its characteristics needs to take into account the areal extent of drought as this study will focuses forward in the piece of writing.

3.2.2 Correlation and concordance analysis

In order to investigate the influence of the aggregation time scale on SPI index, Mckee et al. (1995) compared, for two regions of California and Colorado, values of Palmer index with the SPI aggregated at different time scales *k*; highest correlation coefficients were found for *k*-values of 9 and 12 months. In a similar study, Guttman (1198) also found best correlation between 9 and 12 months, defining this last *k*-value as the one to which is compatible an intrinsic time scale of the PDHI.

For a better understanding of drought detection, Cancelliere et al. (1996) analyzed statistics coming from hydrologic variables as precipitation and streamflow; comparison these with the Palmer index showed that higher correlation coefficients are obtained when drought is valued using the moving average of precipitation calculated at 6 and 12 months and those relative to streamflow at 1 and 3 months.

Referring to drought identification and classification, as previously presented, PHDI, SPI and SSI provide some numerical criteria to detect start and conclusion of drought intervals and to classify drought severity. This is an essential requirement of an index conceived for drought monitoring purposes being helpful for subsequent appropriate mitigation measures of drought effects.

Within the first mentioned criterion falls the correlation analysis; in effect, it is convenient to carry on a concordance analysis among indices by means of correlation analysis. Correlation coefficients are measure of the strength of association between two continuous variables. Correlation measures observed co-variation. It does not provide evidence for causal relationship between the two variables. One may cause the other, as precipitation causes runoff; they may also be correlated because both share the same cause. Evidence for causation must come from outside the statistical analysis, from the knowledge of the processes involved. (Helsel and Hirsch, 2002)

Measures of correlation (here designated in general as ρ) have the characteristic of being dimensionless and scaled to lie in the range $1 \leq \rho \leq 1$. When there is no correlation between two variables, $\rho = 0$. When one variable increases as the second increases, ρ is positive. When they vary in opposite directions, ρ is negative. The significance of the correlation is evaluated using a hypothesis test: H0: $\rho = 0$ versus H1: $\rho \neq 0$.

As an alternative of a punctual correlation among values of indices, this research point out to consider the concordance of indices in order to identify a specific interval as a dry period or not, and on classification of severity assigned to such drought period. The comparison, in this case, is among concordance of two indices in characterizing drought according to various severity levels and at this purpose appears opportune to arrange contingency tables.

Those matrices give information over concordance of two indices and they consent to explore not just probability that indices give same information, but also an indirect evaluation of probability that one of indices characterizes un interval assigning a certain severity class when the other index indicate another one. This method allows valuing the degree of discordance between indices; this degree can be evaluated in an objective manner using specific statistics tests and in particular the τ_b of Kendall.

The methodology can be applied after a preliminary classification of drought magnitude assigned by indices here called *x* and *y*.

Let's consider e.g the following classification of drought severity related to single interval:

- ✓ Mild drought
- ✓ Moderate drought
- ✓ Severe drought
- ✓ Extreme drought

Once calculated values of indices in a specific time period, every time step can be characterized according to the mentioned classification and ultimately carrying a count of intervals in which the *x* index assigns a drought severity class when the *y* index assigns the same or another one.

Those information are reported in a concordance matrix where, for each assessment, is specified the number of time steps allocated in a classification arrangement by the two methods. The categorization assigned by first index *x* is entered in rows *i*, while the one assigned by second method *y* is entered in the columns j. The generic element $O_{i,j}$ of the matrix identifies the numbers of time steps to which has been assigned the class "*i*" from *x*and the class *"j"* by *y.*

In order to carry a closer examination of concordance subsistence at fixed level of statistical relevance, the Kendall test τ_b is an appropriate tool.

Tau (Kendall et al. 1992) measures the strength of the monotonic relationship between two generic variables x and y. It is a rank-based procedure and is therefore resistant to the effect of a small number of unusual values. It is well-suited for variables which exhibit skewness around the general relationship.

Tau (τ) depends only on the ranks of the data and not the values themselves and it can be implemented even in cases where some of the data are censored or missed. This is an important feature of the test for applications to water resources.

The test statistic S measures the monotonic dependence of y on x. Kendall's S is calculated by subtracting the number of "discordant pairs" M, the number of (x,y) pairs where y decreases as x increases, from the number of "concordant pairs" P, the number of (x,y) pairs where y increases with increasing x:

$$S = P - M = \sum_{tutti} \sum\nolimits_{i>x} \sum_{i>y} O_{xy} O_{ij} - \sum_{i>x} \sum_{i>y} O_{xy} O_{ij}$$

where P ="number of pluses", the number of times the y's increase as the x's increase,or the number of $y_i < y_j$ for all $i < j$,

M = "number of minuses," the number of times the y's decrease as the x's increase, or the number of $y_i > y_j$ for $i < j$.

for all i = 1,....(n − 1) and j = (i+1),.....n.

The τ_b correlation coefficient is then given by:

$$\tau_b = \frac{S}{\left\{\frac{1}{2}\left[(N^2 - SS_a)(N^2 - SS_c)\right]^{\frac{1}{2}}\right\}}$$

With:

$SS_a = \sum_{i=1}^{m} A_i^2$ $\qquad$ $SS_c = \sum_{j=1}^{k} C_j^2$

N number of observations and A_i and C_j represent respectively the sum of elements of row i and column j.

A two-sided test for correlation will evaluate the following equivalent statements for the null hypothesis H_0, as compared to the alternate hypothesis H_1:

H_0:

- no correlation exists between x and y ($\tau = 0$), or
- x and y are independent, or
- the distribution of y does not depend on x, or
- Prob ($y_i < y_j$ for $i < j$) = 1/2.

H_1:

- x and y are correlated ($\tau \neq 0$), or

- x and y are dependent, or
- the distribution of y (percentiles, etc.) depends on x, or
- Prob ($y_i < y_j$ for $i < j$) $\neq 1/2$.

To test for significance of τ_b S is compared to what would be expected when the null hypothesis is true. If it is further from 0 than expected, H_0 is rejected. To verify if is not significantly different from zero we need to calculate the standard error:

$$\sigma_s = \sqrt{(n/18)\cdot(n-1)\cdot(2n+5)}$$

The null hypothesis is rejected at significance level α if |ZS| > Zcrit where Zcrit is the value of the standard normal distribution with a probability of exceedance of α/2. Where Z_s is given by:

$$Z_s = \frac{S-1}{\sigma_s} \quad if \quad S > 0$$

$$Z_s = \frac{S+1}{\sigma_s} \quad if \quad S < 0$$

$$Z_s = 0 \quad if \quad S = 0$$

Tau will generally be lower than values of the traditional correlation coefficient r for linear associations of the same strength. "Strong" linear correlations of 0.9 or above correspond to tau values of about 0.7 or above. These lower values do not mean that tau is less sensitive than r, but simply that a different scale of correlation is being used (Helsel and Hirsch, 2002).

3.3 Aggregation of drought indices at River Basin Scale

3.3.1 Overview

It is largely recognized that in many cases no single index can represent all aspects of meteorological or hydrological/water supply droughts and therefore a multi-index approach for operational drought monitoring is needed.

In this section of the study, an aggregated drought indicator able to synthetically describe the condition of an area susceptible of drought events is presented. Such multidimensional drought indicator (called ADI) has been developed with the objective to describe the meteorological, hydrological and agricultural regimes of drought.

Although the methodology can be extended to an arbitrary number of indices, here, with the purpose to detect droughts characterized by deficit of precipitation and streamflow, the Standardized Precipitation Index (SPI), the Standardized Streamflow Index (SSI) and the Palmer Hydrological Drought Index (PHDI) have been selected as the basis of the aggregation.

Whereas PHDI can be calculated just for his monthly time step, SPI and SSI indices can be calculated for several aggregation time scales (1, 3, 6, 9, 12, 18, 24, 36, and 48 months); each of these scales reflects drought impacts to water resources availability: soil moisture is linked to precipitation anomalies in small aggregation time scale, while sub-surface dynamics, streamflow and reservoir management are associated to longer anomalies. The minimum update scale of water management indices is typically a monthly time step. This choice represents an acceptable trade-off between the opposing needs to reduce the influence of small time step fluctuations and to take into account seasonal climatic phenomena.

3.3.2 A multidimensional drought analysis

The ADI proposed, was developed basing on the model originally suggested and calculated by Keyantash and Dracup (2004) for three diverse climate divisions in California; it combines all physical forms of drought with the selection of variables related to different drought type by means of multivariate statistical analysis tools.

Effectively, the ADI developed by Keyantash and Dracup (2004) is a multivariate index, wherein input variables represent the fluctuations in water volume within the hydrologic cycle; most important variables are: rainfall, streamflow, temperature, soil moisture content, potential evapotranspiration, snow water content, reservoir storage volume, and groundwater flow. In its application, ADI incorporates any combination of first six variables; reasons for excluding groundwater and reservoir storage are explained in detail in Keyantash and Dracup (2004); afterwards Keyantash and Dracup, 2004 were able to correlate the ADI with severe droughts identified by the Palmer Drought Severity Index (PDSI).

In the presented research, mentioned variables were involved into the assessment of the proposed indicator throughout combination of different types of drought indices.

Variability of the hydrologic cycle will be described by SSI, SPI and PHDI whose definition requires data of streamflow, temperature and precipitation. Further, in the PHDI formulation, soil moisture and evapotraspiration are considered and estimated with the methodology described in chapter 2.2.2.

The methodology here described is graphically illustrated in following flow chart:

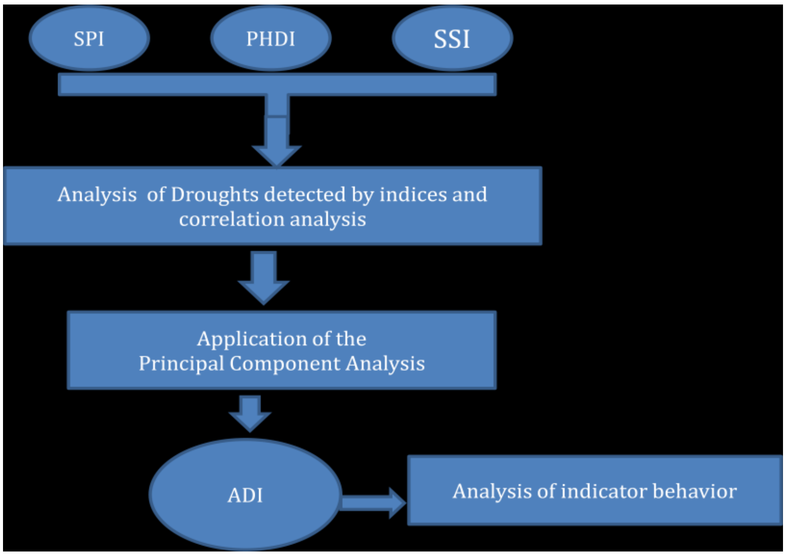

Figure 3.1 – Methodology flow chart

The proposed methodology has been verified at river basin scale where hydrologic and topographical characteristics are homogeneously distributed and more importance is given to the analysis of duration and severity of droughts.

The Principal Component Analysis (PCA) was used to aggregate the aforementioned indices SPI, SSI and PHDI computed for several time scales (1, 3, 6, 9, 12, 18, 24, 36, and 48 months) in order to define the best behavior of ADI.

The principal component analysis is a standard statistical method which the aim is to explain the variance-covariance structure in multiple data sets using a few linear combinations of the original variables. The main objectives are data reduction and interpretation (Kottegoda and Rosso, 2008). It is often used in meteorological studies, to reduce the original intercorrelated variables in a small number of new linearly uncorrelated ones that explain most of the total variance (Rencher, 1998). The new (uncorrelated) variables are called principal components (or PCs scores) and consist of linear combinations of the original variables. The coefficients of the linear combinations are called 'loadings' and they represent the weight of the original variables in the PCs. In brief, this method consists in computing the eigenvalues and the eigenvectors of the covariance matrix, where the eigenvectors, properly normalized, are the loadings (i.e. the spatial patterns), while each eigenvalue tells about the fraction of the total variance explained by each loading (Bordi and Sutera, 2001a and references therein). It must be noted that, under this decomposition, the loadings represent the correlation between the associated PC scores and observation time series.

Therefore, as showed in description of ADI proposed by Keyantash, to compute PCA it is required the construction of a square symmetric correlation matrix that describes the correlations between the original data. Twelve correlation matrices were used, one for each month. These correlation matrices then underwent PCA. An advantage of the correlation-based PCA approach used in the development of ADI is that the ADI is not impacted by the measurement units of the input data, as all input variables are standardized before they are used in the ADI computation.

In detail, per N years and per each month of the time series available, a X matrix is made up with all input index values, previously deseasonlized (deducing the mean value) and normalized (dividing for standard deviation); thus e.g.

$$PHDI^{*} = \frac{PHDI - PHDI_{m}}{\sigma}$$

$$X = \begin{bmatrix} SPI^{*} & PHDI^{*} & SSI^{*} \\ SPI^{*}{}_{1} & PHDI^{*}{}_{1} & SSI^{*}{}_{1} \\ \vdots & \vdots & \vdots \\ SPI^{*}{}_{n} & PHDI^{*}{}_{n} & SSI^{*}{}_{n} \end{bmatrix}$$

Thus a square and symmetric correlation matrix is assembled with all considered parameters, obtaining twelve matrices, one for each month, made in this way:

$$\begin{bmatrix} & SPI^{*} & PHDI^{*} & SSI^{*} \\ SPI^{*} & 1 & \cdots & \cdots \\ PHDI^{*} & \cdots & 1 & \cdots \\ SSI^{*} & \cdots & \cdots & 1 \end{bmatrix}$$

Lastly, by means of PCA, eigenvalues, and related eigenvectors, are derived from the correlation matrix. Per each month eigenvectors coupled with first eigenvalue are defined as:

$$e^{I} = [e_{1}\ e_{2}\ e_{3}\ e_{4}\ \ e_{5}\ e_{6}]$$

The principal component (greatest eigenvalue) is used to select the associated eigenvector to derive the ADI. The ADI is ultimately computed as:

$$a = \frac{X\ e^{I}}{\sigma}$$

where a is a time series array of derived ADI values, X is the matrix of deseasonalized hydrologic parameter data, e_I is the eigenvector associated with the principal component derived from the correlation coefficient matrix, and σ is the standard deviation of the array derived from the product of X and e_I.

As was done by Keyantash and Dracup (2004), the ADI was considered as the first PC (PC1), normalized by its standard deviation:

$$ADI_{i,k} = a_{i,k}$$

where, $ADI_{i,k}$ is the ADI value for month k in year i, $a_{i,k}$ is the first PC during year i for month k.

The ADI utilizes only the PC1 because it explains the largest fraction of the variance described by the full p-member standardized data set.

3.4 Probabilistic Characterization of Drought Areal Extent Based on SPI

3.4.1 Overview

In this paragraph, a methodology for the probabilistic characterization of drought spatial extent is presented.

More specifically, a method to characterize probabilistically the relationship between drought severity (computed in terms of Standardized Precipitation Index, SPI) and areal extent, expressed as drought Severity-Area Frequency (SAF) curves, is proposed. A drought SAF curve describes the proportion of the total area of the region under investigation where the SPI values are below a fixed threshold. Then the probability of observing a given curve is derived analytically. This enables to characterize a given drought event in a region, by computing the probability of occurrence of SAF curves exceeding the one observed.

Although the methodology has been developed with reference to SPI, it can be easily extended to other indices such as PHDI.

3.4.2 Analysis of areal drought extent

In order to achieve the stated objective, the SPI is adopted to assess drought occurrence and to value its regional extent in Sicily. The SPI offers the capability to monitor climatic conditions over a wide spectrum of time scales and to compare index values over different locations. Further it just needs precipitation data to implement its calculation.

Observation time series of the considered hydrologic variable are limited to gauge stations spread all over the regional area under study, therefore, as first step, it is essential to select the method to account for the spatial variability of the considered variable This can be carried out by interpolating the at-site information over a regular grid by means of a space-time model of the basic hydrologic process. Alternatively, as presented ahead in this research, weights can be assigned to each station, for instance by means of Thiessen polygons method. Gridded data can be considered a special case of the latter, where equal weights are assigned to each cell.

Once selected the measurements stations, the procedure considers to elaborate the selected drought indicator, the SPI. As remembered above, the SPI is based on an equi-probability transformation of aggregated monthly precipitation into a standard normal variable. In practice, the index is computed by fitting a probability distribution on aggregated monthly precipitation series and by computing the corresponding non-exceedance probabilities and standard normal quantiles, the latter defined as the SPI series. A drought event is considered to occur at a time when the value of SPI is continuously negative and ends when SPI becomes positive. (Mishra and Singh, 2009).

For a given interval t, two indices are computed, representative of the areal extension and amount of the deficits over the investigated region.

The Figure 3.2 depicts a scheme of the regional extension of the methodology. In particular, once the threshold levels *ho(k)* for each site *k=1....K* are defined, it is possible to identify for each interval L sites which present deficit, i.e. sites for which the difference between the threshold and the observed value of the variable is positive:

$$H_0(k) - h(i,k)$$

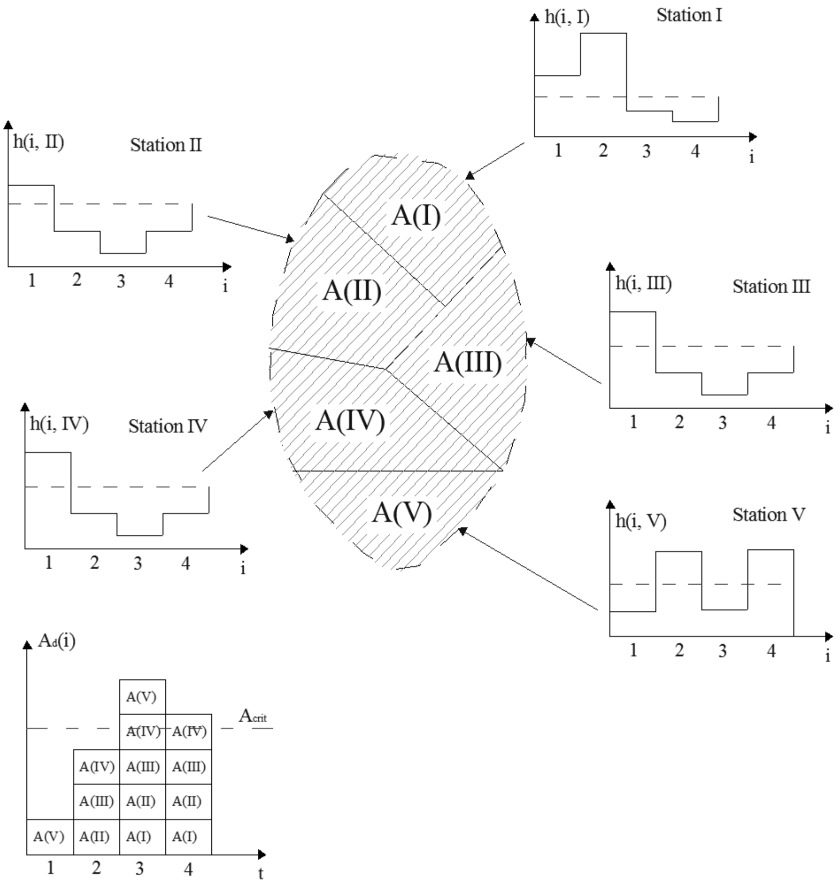

Figure 3.2 – Regional drought identification (adapted from Rossi and Cancelliere 2003)

In order to probabilistically model magnitude and areal extent of droughts, first drought areal extent will be defined as a function of drought severity.

To this end, let us consider a region with M rainfall stations. Assuming a fixed aggregation time scale, let $Z_{j,t}$ the SPI value at month t, in station j, and A_j the related influence area computed for instance making use of Thiessen polygons (Figure 3.2). With reference to a SPI threshold z_0, drought areal extent in a given month t can be expressed as:

$$A_t(z_0) = \frac{\sum_{j=1}^{M} I\left[Z_{j,t}\right] * A_j}{\sum_{j=1}^{M} A_j}$$

With $I\left[Z_{j,t}\right] = 1 \; if \; Z_{j,t} < z_0 \, and$ 0 otherwise.

At(z_0) represents the percentage of regional area affected by a SPI≤z_0.

Then, in a given month, the drought Severity-Area-Frequency curve in a region will be given by the plot of areal extent At(z_0) vs. z_0.

In synthesis, the following steps are proposed as procedure for deriving Severity-Area-Frequency curves:

- ✓ Selection of precipitation stations to be involved in the regional analysis in order to compute the SPI monthly time series and calculate associated influence areas;
- ✓ compute related SPI estimating a measure of drought severity (e.g. sum of negative runs in a dry spell, sum of negative SPI values in a dry spell, etc.) associated with different areal extents (in terms of percentage area) by considering different areal threshold;
- ✓ performing frequency analysis for each drought areal extent thresholds (in terms of percentage of total regional area) considering an adequate probability distribution;
- ✓ associate drought severity extent with several probability thresholds and construct the drought severity-area-frequency (SAF) curves in order to carry on a regional analysis.

CHAPTER 4

4 INVESTIGATED AREAS AND AVAILABLE DATA

4.1 Introduction

Methodologies previously presented have been applied in the Mediterranean region of Sicily in order to study and analyze occurred droughts and to extract information helpful to a deeper understatement of methods and characteristics.

In this chapter, before coming with the application, selection of data time series are presented as essential requirement for indices calculation and comparison.

Methodologies have been applied at two different spatial scales and areas of study which are here presented: the whole region of Sicily and the Acate River watershed in the south-east of Sicily.

4.2 Localization and geography of Sicily

The methodology relating to the probabilistic analysis of areal severity extent of drought has been applied to the Italian region of Sicily; it is localized in the Mediterranean Sea to which is the largest island (25,426 sq. km).

Briefly, the orography of the island is prevalently mountainous and hilly; the highest mountains lie in the north-east, with Mount Etna (3,340 m.), rising between the Catania plain and the Alcantara and Simeto river valleys, and the Sicilian Apennines. The Sicilian Apennine range of mountains is divided into three groups: along the northern coast, mountain ranges of Madonie (2000 m) Nebrodi (1800 m), and Peloritani (1300 m). At the foot of the south slope of Etna lies the Catania plain, delimited to the south by the Iblei hills (1000 m), a wide expanse of high ground culminating in Mount Lauro (986 m.). The middle of the island is a broken succession of rolling hills (Erei lying among the Catania plain, the Iblei and the Salso valley).

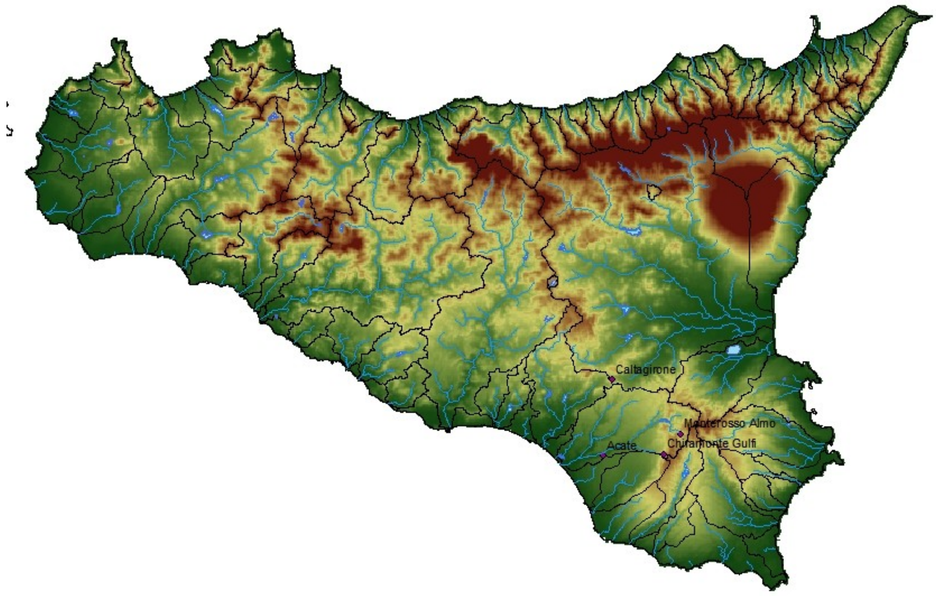

Figure 4.1 – The physical map of the island of Sicily with main river watersheds.

In Sicily climate is Mediterranean, with hot dry summers and mild wet winters. Precipitations are confined mainly to the winter months. Rainfall is low particularly on the low-lying ground round Catania and Gela.

The island is drained by several rivers, most of which are fast flowing with an irregular volume of water, flash flooding in winter and long periods of drought. The principal rivers are the Simeto (which channels the waters of the Dittaino, Gornalunga and Caltagirone), the Alcantara, Anapo, Cassibile and Tellaro, on the Ionian sea in west side; the Torto and San Leonardo, flowing into the Tyrrhenian Sea in north side, and the Belice, Platani and Salso which empty at south into the Sicilian Sea.

Table 4.I – Longest rivers in Sicily

River	Length (km)	River	Length (km)	River	Length (km)
Salso	144	Gornalunga	81	Dirillo	54
Simeto	113	Gela (river)	74	Verdura	53
Belice	107	Salso Cimarosa	72	Alcantara	52
Dittaino	105	Torto	58	Tellaro	45
Platani	103	Irminio	57	Anapo	40

4.3 The gauge stations network in Sicily

The drought analysis has been carried out using long records of precipitation and temperature measurements. The monthly data used in the procedure above have been extracted from the longer database available at the Department of Civil and Environmental Engineering (DICA) of the University of Catania.

Precipitation data

The data base consists of precipitation data registered in the Annual Register of the Sicilian Hydrographic Office; in such dataset of measures there is highly variable with differences from year to year since there are missing data rather than some stations with historical records that have been replaced by up to date tele-metering rain stations. Anyhow this network has been selected, rather than other ones, because of the size of its time series and the quite uniform spatial distribution of the stations considered over the region. Once the preliminary selection of stations was achieved, a check on the network spatial coverage of Sicily region has been carried out.

The pluviometric database of DICA was originally made up of a selection of 173 stations within the whole network of the Hydrographic Service and uniformly distributed in Sicilian watersheds. Coherently with last Register publication of the Hydrographic Service, the database has been updated until end of 2005.

Nevertheless, most of 173 stations selected in the original database, in last years have been dropped while other stations have been replaced with a different or more modern instrumentation service (like telemeasurements; e.g in 2004 were active 110 traditional station over 173, in 2005 95/173, and 2006 75/173).

The Hydrographic Service post daily measurement on his website, where there are available information coming from around 100 modern station in telemeasurement; some of them have effectively replaced some of 173 traditional station originally selected by DICA.

Thus, due to such evolution of available rain stations of the Service, the historic database has been narrowed to 105 stations (Figure 4.2), to which are available significant records of historical time series of 84 years of precipitation data at monthly time scale (from 1921 to 2005).

Figure 4.2 - Localization of rain stations all over the Sicily area.

In extracting records, the selection of rainfall stations has been carried out according to the criterion of spatial distribution of the stations to allow an homogeneous spatial coverage of the area under study with a presence of almost one station in every river basin as showed in Figure 4.2.

At each rain station has been associated an influence area, calculated using the methodology of Thiessen polygons, thus considering as borders of areas the axis of segments linking gauge stations. (Figure 4.3)

The worth of this methodology is that it permits to divide the regional territory in fixed and unbiased influence areas even if in this way it is not possible to consider the morphology of the country.

Figure 4.3 – Thiessen polygons associated to each selected rain station.

The quality of the data of historical database has been checked by Alecci and Rossi (2007) through a double mass analysis and few tests of randomness, which led to a selection of the longest and more reliable series (Alecci *et al*., 2007).

In following Figure 4.4 been traced out the monthly variability of rainfall.

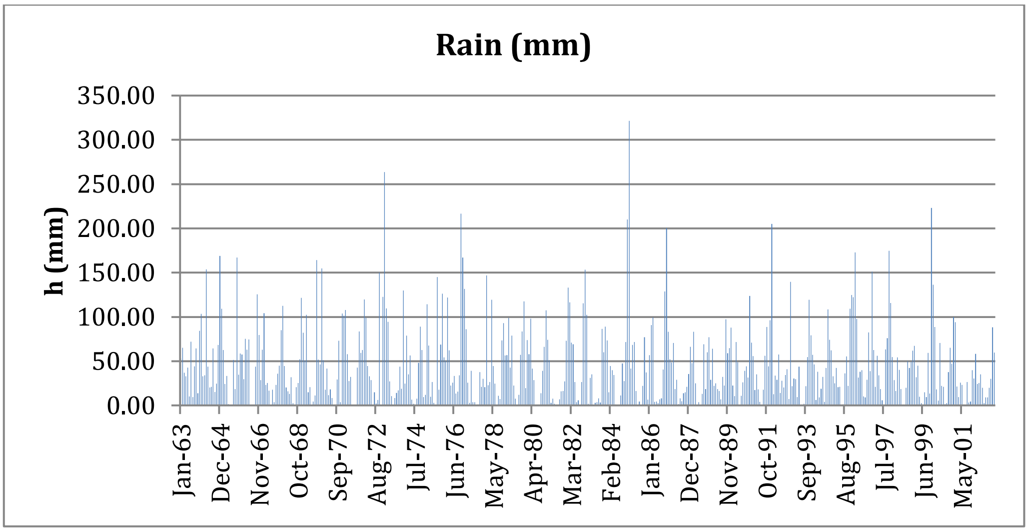

Figure 4.4 – Spatially averaged montly rain registered over the Acate River basin

Missing data in the original records were estimated by using linear regression equations fitted to the available monthly data observed at the station and at a nearby reference station. In particular, when contemporary data have been recorded, correlation coefficients between the annual precipitation observed at a given station and few neighbor stations were evaluated. Then, the site with the highest correlation coefficient was selected as reference station and missing monthly data at the station of interest were estimated by using 12 linear equations, one for each month.

4.4 The Acate River Basin

4.4.1 Localization

Since it has been researched extensively for various catchment management activities, the Acate River basin, in Sicily, has been considered to validate the methodology inherent the aggregation of indices.

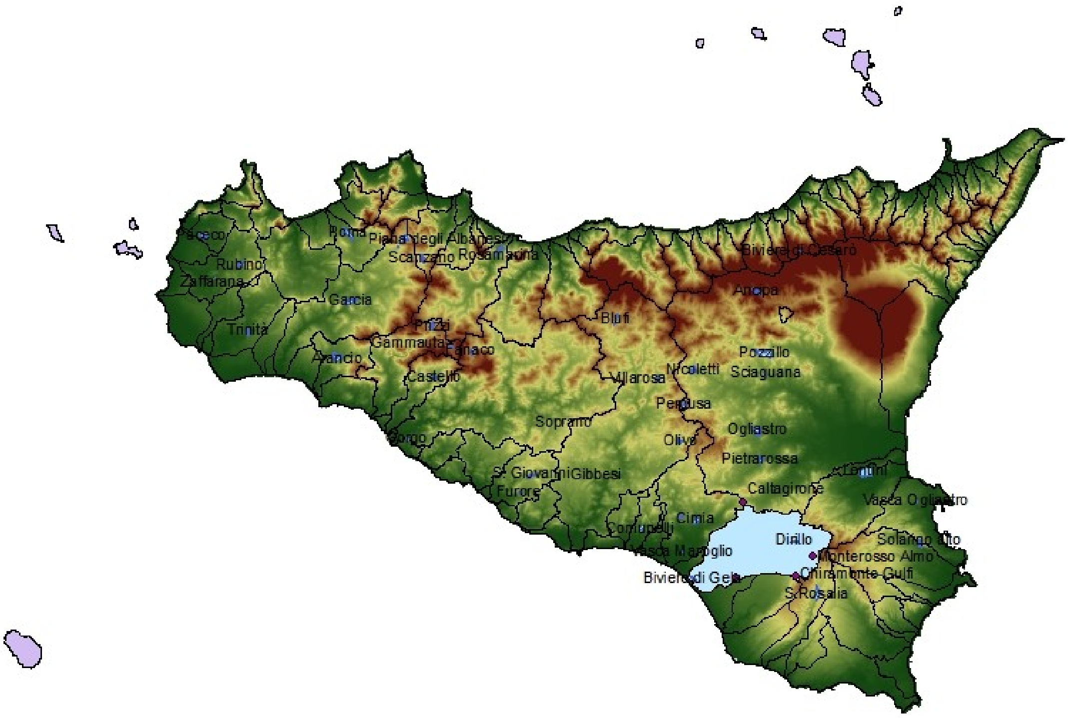

Figure 4.5 – Localization of the Acate river basin within the island of Sicily

The Acate River watershed (so-callled also Dirillo or Amerillo in the mountain side) is located in the south-east side of Sicily and its extension is around 385 Km^2, covering the administrative counties of Ragusa, Catania and Caltanissetta. The basin includes municipalities of Vizzini, Monterosso Almo and Licodia Eubea. The city of Caltagirone is just outside the watershed border, but it was included in this study since it has long records of precipitation and temperature functional to this research.

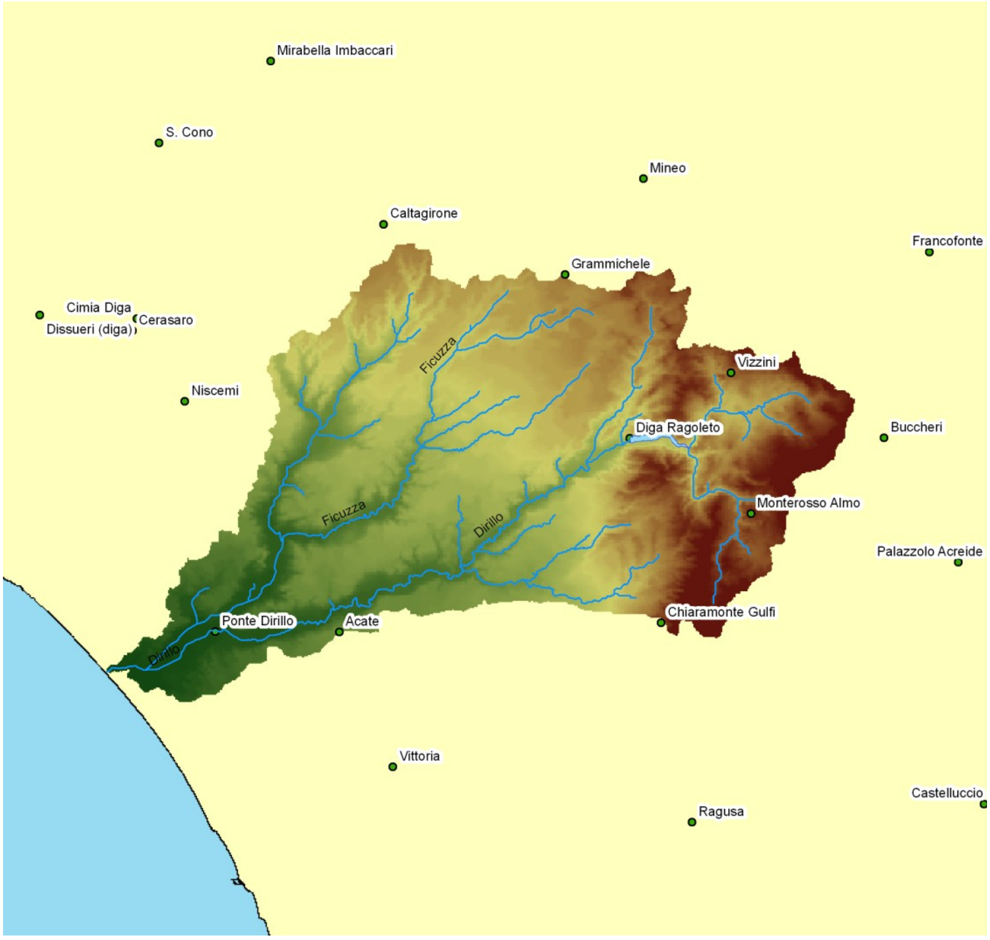

Figure 4.6 – The Acate River watershed.

4.4.2 Available data in gauged stations

Dataset for this application is constituted by precipitation, temperature and streamflow measurements. Available time series have records of 40 years from 1963 to 2002.

Precipitation dataset

Within the Acate River watershed, fall over the rain gauge stations named Vizzini, Monterosso Almo, Chiaramonte Gulfi, Licodia Eubea and the Ragoleto Dam

Table 4.II – Pluviometric rain gauge station within the watershed of Acate river.

Gauge Stations	Height (m a.s.l.)	Working period	Available years	Annual mean precipitation
Licodia Eubea	630	1963-76	1963-1976	606,8
Chiaramonte Gulfi	672	1921-41; 51-93;95-03	1921-2003	765,1
Monterosso Almo	667	1924-41; 51-03	1921-2003	705,8
Diga Ragoleto	331	1977-2000	1977-2000	539,6
Vizzini	581	1921-41; 58-80; 82-89; 91-2000	1963-2000	589,4
Caltagirone		1921-2003	1921-2003	539.83
Acate		1921-1952,1958-2003	1921-2003	530.78

Nevertheless, some of these rain stations are not helpful because of short time series records; therefore selected rain gauge stations for the application were restricted to Caltagirone, Monterosso Almo, Acate and Chiaramonte Gulfi.

Hence, data processing was carried out to obtain the catchment representative monthly values. The four rainfall measuring stations were used to compute the monthly evaporation values for the catchment. Of the four measuring stations, one was outside of the catchment area; however, it was considered in the analysis as it is very close to the study area and no other gauges with relevant dataset were present in the northern part of the catchment.

Following the method called “interpolate-calculate”, drought indices have been calculated once precipitation data were spatially distributed. The commonly used Thiessen polygon method (Thiessen, 1911) was used to spatially average data calculating each gauge station influence areas and subsequently monthly rainfall and temperature values for the catchment.

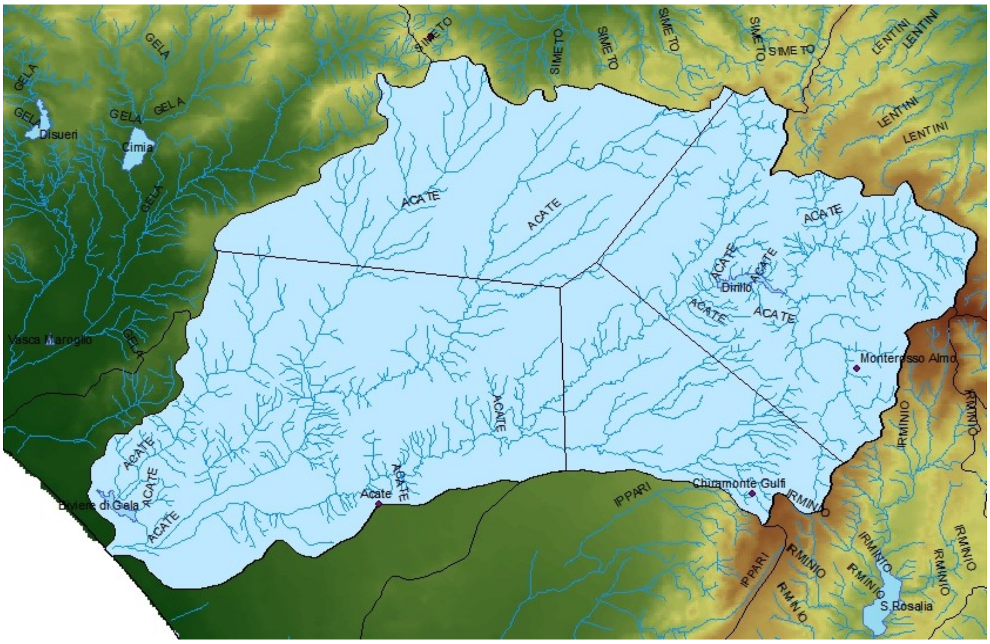

Figure 4.7 – Partition of the Acate river basin in influence areas with Thiessen polygons

Temperature dataset

As illustrated in the paragraph 2.2.1, the Palmer method requires not just data related to precipitation time series but also the continuous monthly temperature time series; this exigency narrows the number of available stations, since in Sicily number of thermometric measures is much lower than pluviometric observations. The only available thermometric stations within the watershed are:

Table 4.III – Thermometric gauge stations within the watershed.

Thermometric Stations	Height (m s.l.m.)	Working period	Annual mean temperature (°C)
Caltagirone	513	1963-2004	16,5
Monterosso Almo	667	1961-2002	15,6

Missing data of thermometric series were integrated valuing data in a neighbor station and taking into account differences between monthly mean values in that observation period. This simplified method value the variable *A* in the time interval *i,* depending on the observed value in one or more neighbor stations and applying monthly corrective parameters elaborated in the coeval working period of stations.

$$T_{jA} = f_{jAB}(T_{jB})$$

This corrective parameter is given by the difference between monthly mean values observed in the two stations:

$$T^{h}{}_{\mu,\tau} = T^{k}{}_{\mu,\tau}\frac{\overline{T^{h}_{\tau}}}{\overline{T^{k}_{\tau}}}$$

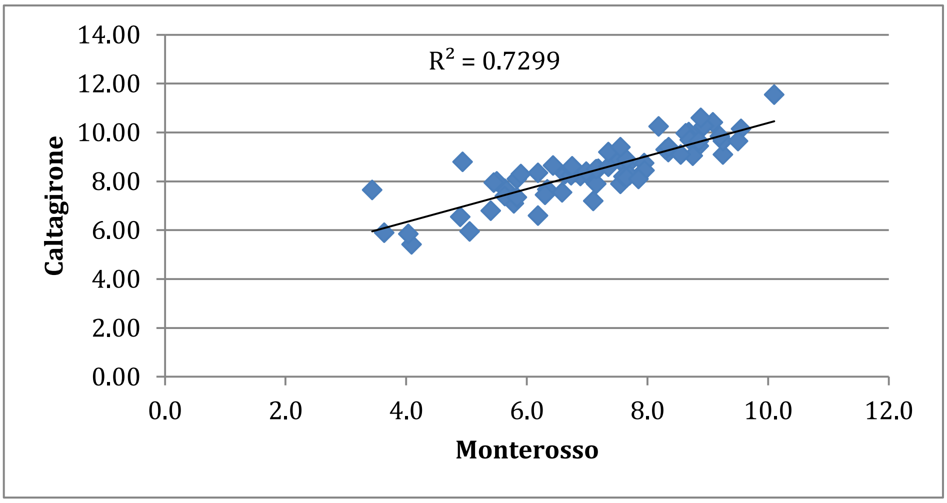

Figure 4.8 - Linear regression for the elaboration of temperature missing data in the two available thermometric stations of Caltagirone e Monterosso Almo

This method is necessary in order to estimate missing temperature data, since the spatial stationarity hypothesis cannot be applied, and the variable values depend significantly on altitude.

Data in the other two stations, Acate and Chiaramonte Gulfi, have been reconstructed using parameters that were estimated by Bonaccorso et al. (2007) that detected trends on temperature and related the variable to the height above sea level deriving the experimental monthly semi-variogram as seen in Figure 4.9

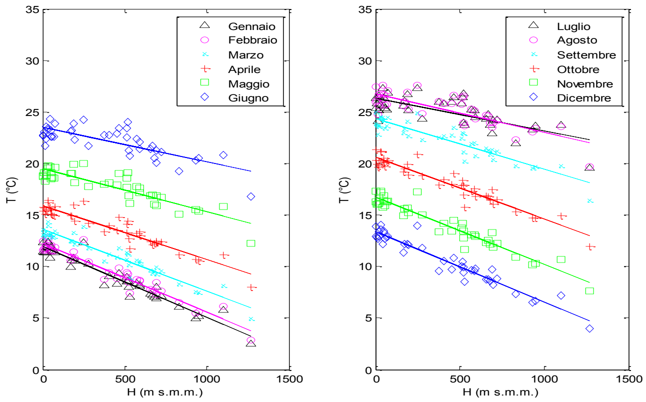

Figure 4.9- Experimental variogram for calculation of missing temperature data depending on altitudevariation in the stations of Chiaramonte Gulfi and Acate (Bonaccorso et al. 2007)

In the Figure 4.10 are traced out the mean annul values of air temperature registered at the gauge stations and then spatially averaged over the Acate river basin:

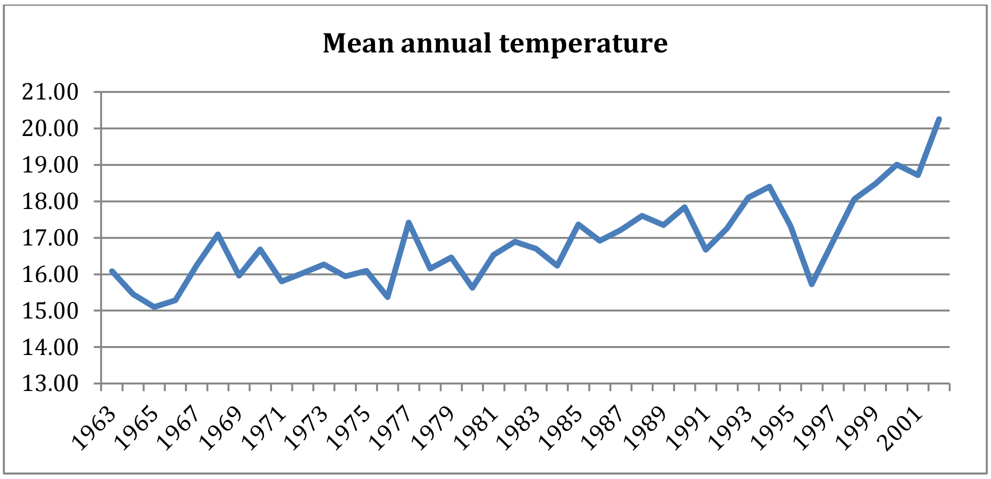

Figure 4.10 – Mean annual temperature registered at stations of the Acate River basin.

Streamflow data

Finally streamflow data were reconstructed by means of simulation of the water balance at Ragoleto Dam. Daily streamflow data at Ragoleto Dam were used in this study as they were considered as the catchment representative data, to account for the fluctuations in streamflow discharge. This station was used as it had long records of flow measurements and also it is a good representative station in the Acate River main stream

The Ragoleto Dam, build in 1962, is located upstream in Acate river, and it has a watershed of 117,5 Km^2

In order to value the stream-flow of Acate River, considered as the inflow at the Ragoleto reservoir, a water balance relationship has been elaborated. For a generic month *i,* the balance is*:*

$$V_{di} = I_i - I_{i-1} + U_i + E_i + P_i$$

Were volume (V_d) of runoff at month *i* has been calculated taking in account reservoir volume (I), derived volume (U_i), evaporation (E_i) and water leakage due to other causes (overwhelm, flashing, etc)

In the Appendix is reported the **Errore. L'origine riferimento non è stata trovata.** where are summarized the reconstructed streamflow at Ragoleto Dam.

In following Figure 4.11 is traced out the remodeled stream-flow of the Acate River:

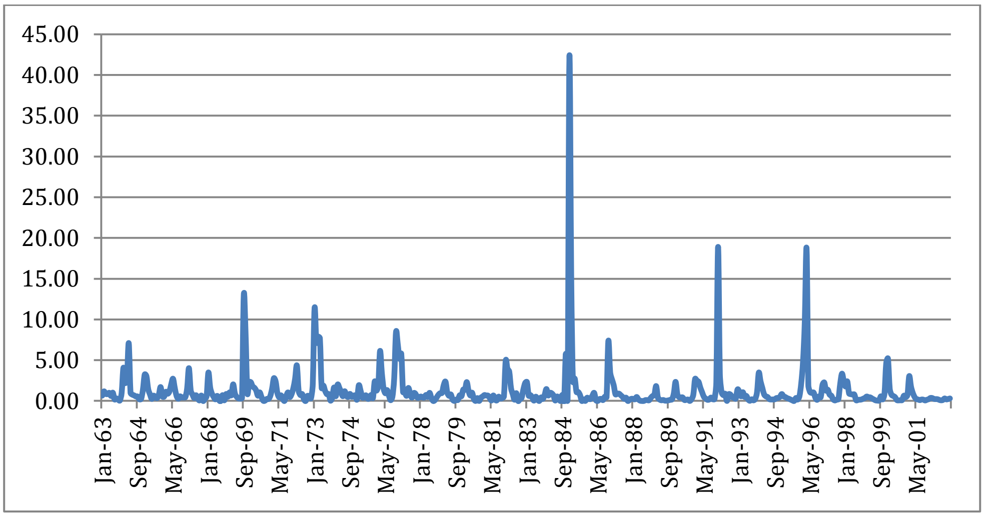

Figure 4.11 – Streamflow at Ragoleto Dam over the Acate River.

CHAPTER 5

5 COMPARISON OF DROUGHT INDICES

5.1 Introduction

The objective described in the current chapter is related to the comparison of selected drought indices over the spatial scale corresponding to the illustrated Acate river catchment.

Input variables of the proposed indicator represent in an indirect manner the fluctuations in water volume within the hydrologic cycle; effectively, selected indices to be aggregated are the Standardized Precipitation Index (SPI), the Standardized Streamflow Index (SSI) and the Palmer Hydrologic Drought Index (PHDI) for which computation hydrologic parameters as rainfall, stream-flow and air temperature are considered necessary. Furthermore, within the elaboration of PHDI, soil moisture content and potential evapo-transpiration are estimated as suggested by Palmer (1965) and outlined above in the paper.

In the progress, calculation of indices is outlined and drought characterizing parameters are elaborated and discussed throughout a correlation and concordance analysis.

5.2 Computing selected drought indices

Watershed description has been reported in the previous chapter, and data measurement locations for rainfall, stream-flow and air temperature are shown in Figure 4.3; related datasets used in the various computations of indices refer to the same observation period ranging from January 1963 to December 2002 (40 years) with the purpose to obtain comparable elaboration results. With the same goal, in order to conduct a comparable statistical analysis between indices, just a reduced numbers of years have been considered; in effect, in the calculation of SPI and SSI indices, for aggregation scale of k-months, there are no index values for k-1 months. Further in this way, first years of the Palmer index series are discarded since they are excessively sensible to the initial soil moisture condition (Guttman, 1991).

5.2.1 SPI and SSI indices

Mentioned indices SPI, SSI and PHDI were calculated over the study area at monthly time step: this for various reasons including easier access of monthly data and lower sensitivity to observational errors; subsequently precipitation and stream-flow time series were elaborated for several aggregation time scales (1,3,6,9,12,18,24,36 e 48 months).

Computation of indices has required elaboration of specific MATLAB® codes some of them, regarding the SPI procedure of calculation, previously settled for other studies by Bonaccorso.

Exploiting the flexibility of the index calculation, nine time series of SPI and SSI have been investigated, one for each *k* value of aggregation scale; the choice of one of them leads to detect different typologies of drought and permits to analyze various aspects of hydrologic cycle.

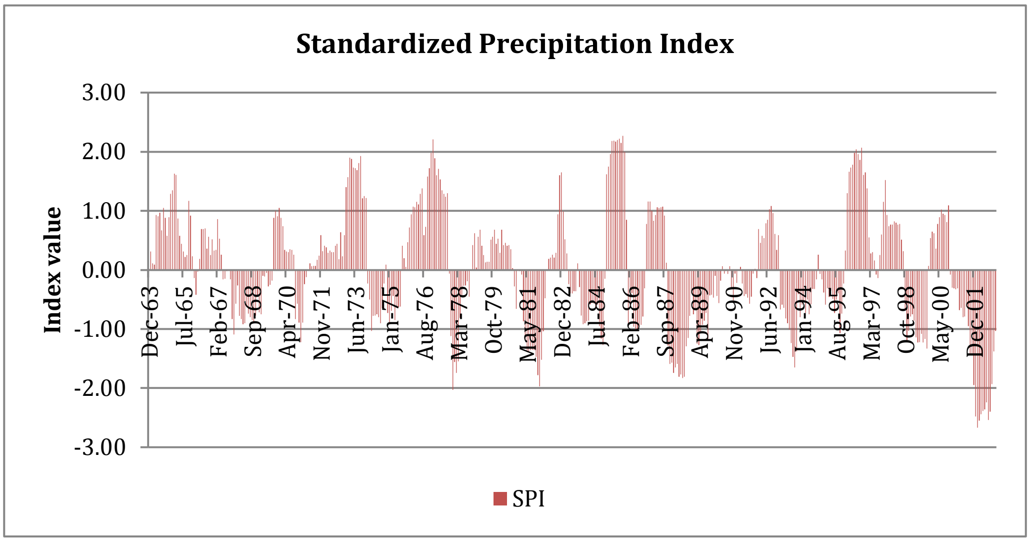

Figure 5.1 – SPI index computed at the aggregation scale k=12 in the Acate River catchment

Table 5.I – Characterizing parameters of drought identified by SPI (k=12) and assigned drought classes

	SPI (k=12)								
	Drought duration T (months)	$\sum_{Tk}$ "Cumulative Index"	**Min_k**	**$\sum_{Tk}$/T "Magnitude"**		**Mild** 0.0	**Moderate** -1.0	**Severe** -1.5	**Extreme** -2.0
number	21					33	19	6	2
Min	1	-37.00	-2.67	-1.42		1	1	1	1
Mean	11.43	-9.06	-0.79	-0.60					
Max	30.00	-0.14	0.00	-0.05		21	7	9	9
Total	240	-190.2				171.0	41.0	18.0	10.0

In Figure 5.1 and Figure 5.2 are represented typical plot of the SPI and SSI indices with detected drought when values are lower than zero. The drought identification criteria proposed by MacKee et al. (1993), require two conditions:

SPI > 0,0 and $SPI_{min} \leq -1$.

The same criteria have been adopted for the SSI index.

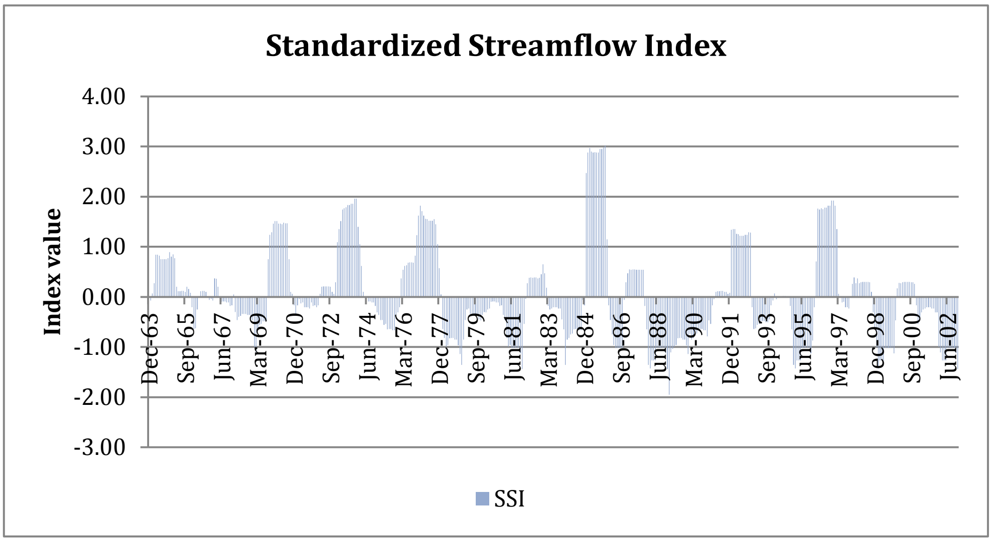

Figure 5.2 – Time series of SSI values obtained for an aggregation scale of k=9.

Table 5.II - Characterizing parameters of drought identified by SSI (k=9) and assigned drought classes

SSI (k=9)

	Drought duration T (months)	$\sum_{Tk}$ "Cumulative Index"	**Min_k**	**$\sum_{Tk}$/T "Magnitude"**		**Mild**	**Moderate**	**Severe**	**Extreme**
						0.0	-1.0	-1.5	-2.0
number	27					32	5	1	0
Min	1	-18.18	-2.67	-1.42		1	1	1	0
Mean	12.78	-4.63	-0.79	-0.60					
Max	44.00	-0.41	0.00	-0.05		14	5	2	0
Total	209	-190.5				142.0	51.0	4.0	12.0

Some of application results have been plotted in following figures where is possible a qualitative comparison between SPI at different *k* values.

Observing Figure 5.3 is quite evident as increasing the aggregation time scale, different behaviors of the SPI index are highlighted: in correspondence of small *k* values drought periods identified are shorter but with a higher frequency respect to those detected by SPI calculated using higher *k* values.

Analogues comments can be expressed about the behavior of SSI index.

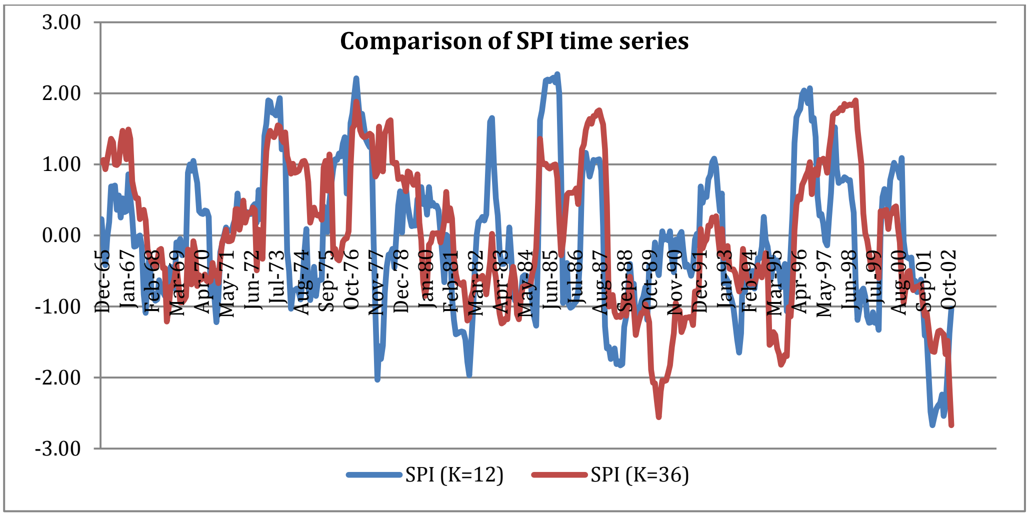

Figure 5.3 – Comparison of SPI series at different aggregation scales (k=12 and k=36).

The SPI and SSI indices can be assumed as a measure of drought severity: in effect the sum of index values calculated over the whole drought period could effectively represent the deficit (of precipitation and runoff); further the deepest index value can be considered as a measure of the maximum value of drought intensity.

In order to identify the typology of drought and to investigate different aspects of the hydrologic cycle, the choice of the most appropriate time scale is relevant; thus, a correlation analysis is arranged in order to extensively investigate drought features described by aforementioned indices.

5.2.2 The Palmer Drought Index

Calculation of Palmer index has been done by means of rain and air temperature time series registered at the four stations of the Acate river basin from 1963 to 2002.

Unlike SPI and SSI, the PHDI can be computed just a monthly time scale and its elaboration has been made using Fortran® codes written and proposed by Alecci.

Soil moisture measurement data were not available, and therefore the two-layer water budget model of Palmer (1965) was adopted in this study to determine the soil moisture content in the catchment. In his computation, a hydrologic soil balance needs to be elaborated and for this purpose the knowledge of the available water capacity (AWC) is essential. It measures the soil water contents range of values in which vegetation roots are able to withdraw water. The AWC depends on soil structure, weave and vegetation coverage.

In order to specify the AWC range of value, this study refers to applications of Alecci et al. (2007) that estimates AWC basing on review over soil structure variability in Sicily (Fierotti 1997) and in Santoro (1991) that assumes typical values of AWC in correspondence of several combination of soil structure and exploitation.

The AWC value for the Acate river has been evaluated in 125 mm. Anyhow Alecci et al. (2007) evaluated the sensitivity of PHDI associated to a range of AWC values; results showed that the index is obviously sensible to AWC given that the method is based on hydrologic soil balance, but the influence is slight for mild drought class, while is more sensible for identified drought that fall in the other three classes.

The potential monthly evapotranspiration PE (mm) has been evaluated using the Thornthwaite formula described above in the § 2.2.1.

Due to temperature condition, therefore to evapo-transpiration level, the two layer of soil are subjected to reduce them water content even if with different intensity.

Once computed the hydrologic balance, the elaboration of the Palmer index has been achieved; in the Figure 5.4 is plotted the PHDI time series where is possible to detect most important drought periods enlighten when graph is under the x-axis.

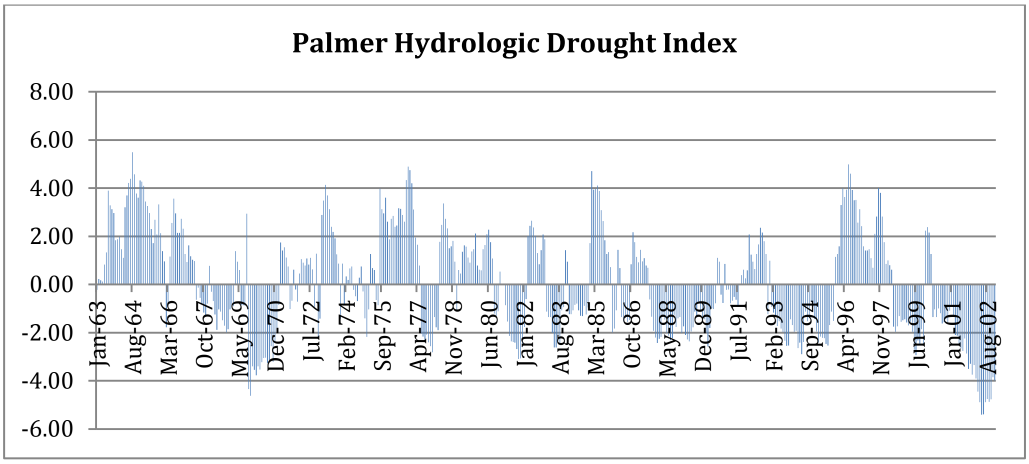

Figure 5.4 – Historical time series of PHDI index computed over the Acate River watershed

Table 5.III – Characterizing parameters of droughts identified by PHDI and assigned drought classes

PHDI

	Drought duration T (months)	$\sum_{Tk}$ "Cumulative Index"	**Min_k**	**$\sum_{Tk}/T$ "Magnitude"**		**Mild** 0.0	**Moderate** -1.0	**Severe** -1.5	**Extreme** -2.0
number	27					39	19	5	2
Min	1	-83.61	-5.41	-3.64		1	1	1	1
Mean	7.30	-15.46	-2.12	-1.70					
Max	25.00	-1.02	-1.00	-1.02		11	7	10	8
Total	197	-417.5				106.0	61.0	20.0	10.0

5.3 Correlation analysis of indices

Each of the computed SPI and SSI indices shows a different typology of drought event. Nevertheless a preliminary analysis done by graphic evaluation of indices, shows an important degree of concordance in the behavior of indices, in the example in Figure 5.5 computed at the same aggregation scale (k=12), as revealed.

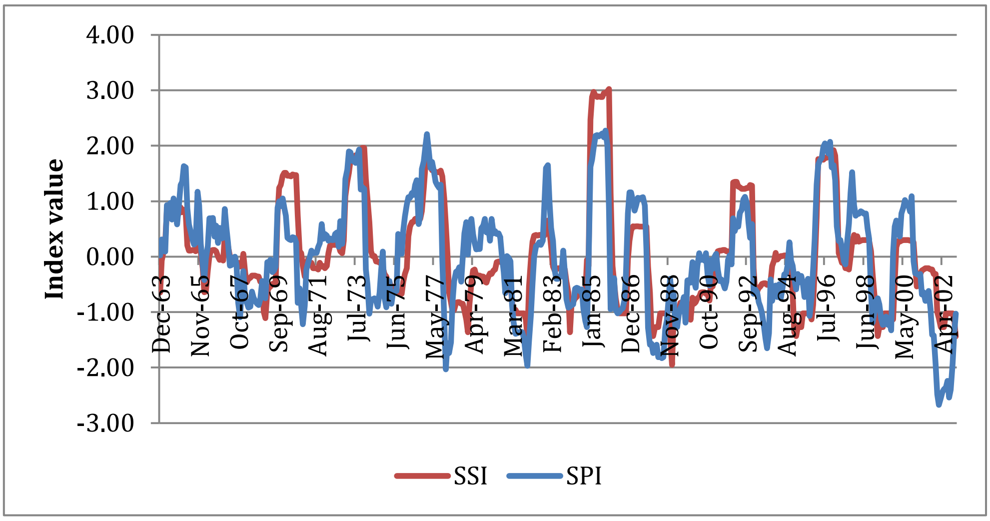

Figure 5.5 – Comparison between SPI and SSI calculated at k=12

Furthermore a comparison of values between SPI and SSI has been carried out by means of linear correlation analysis obtaining, as easily considered, not always a good correlation between indices.

In Table 5.IV are summarized values of linear correlation related to all possible combination between indices. Correlation values range is from 0.079 for SSI-1 and SPI-48 to 0.797 in correspondence of SSI-36 and SPI-36.

Table 5.IV Correlation table between SSI and SPI at different aggregation scales.

r	**SPI1**	**SPI3**	**SPI6**	**SPI9**	**SPI12**	**SPI18**	**SPI24**	**SPI36**	**SPI48**
SSI1	0.215	0.281	0.239	0.228	0.203	0.149	0.131	0.100	0.079
SSI3		0.429	0.504	0.496	0.467	0.340	0.326	0.251	0.193
SSI6			0.646	0.709	0.674	0.515	0.463	0.357	0.254
SSI9				0.746	0.790	0.652	0.547	0.440	0.303
SSI12					**0.779**	0.726	0.601	0.476	0.328
SSI18						0.775	0.725	0.539	0.373
SSI24							0.782	0.603	0.446
SSI36								**0.797**	0.575
SSI48									0.793

A graphic representation of some of the correlation relationship between SPI and SSI is shown in Figure 5.6:

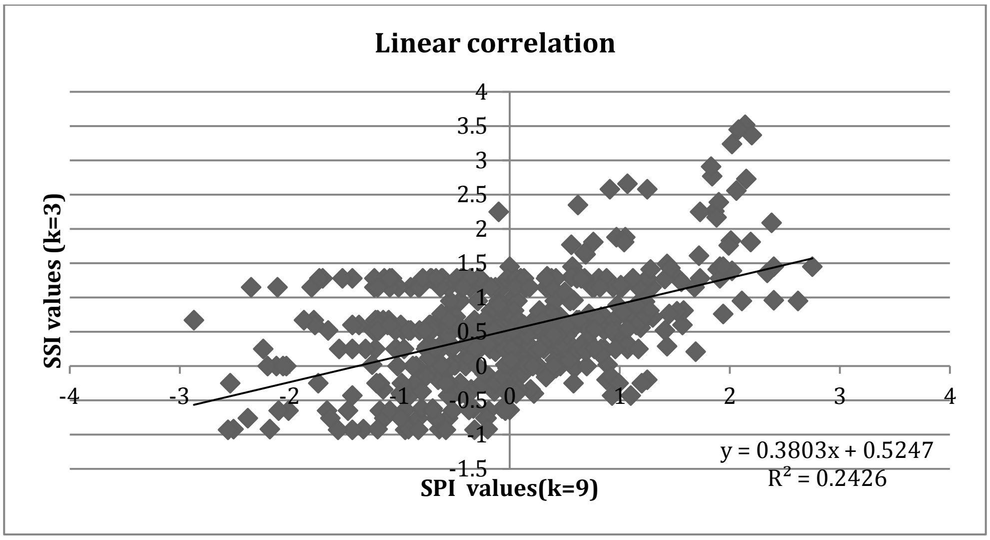

Figure 5.6 - Chart of the linear correlation of SPI and SSI elaborated over the Acate River watershed.

A good correlation for high *k*-value of aggregation scales, imply that the SPI might be considered not just a meteorological index but even an indicator of hydrologic droughts. Validation of such hypothesis, require a closer investigation of concordance relationship between SPI and SSI in the allocation of identified drought period in classes established.

A qualitative and quantitative comparison, between characteristics of identified droughts, has been made referring to introduced indices.

Observing the graph of the normalized PHDI (called PHDI*) and SPI, they visibly agree in classifying drought circumstances in despite that classes are settled following different parameters; further, considering the SPI index at the aggregation scale k=12, it generally reveal values halved respect to the PHDI index that instead classify droughts in a more severe manner.

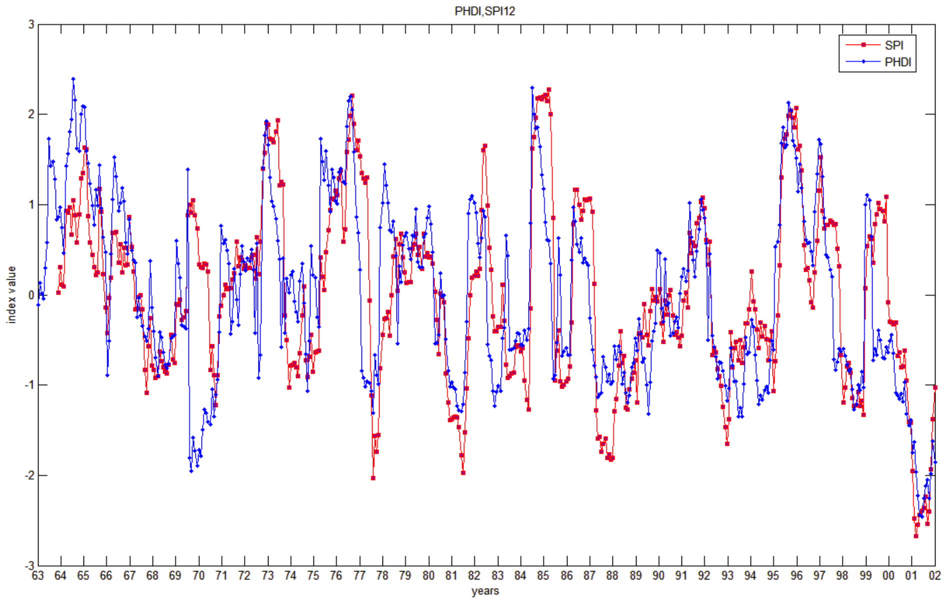

Figure 5.7 – Comparison between time series of the SPI (k=12) and the normalized PHDI*.

As previously reported, SSI has a high concordance with the SPI; the aggregate drought indicator delineates his trace in the midway and his behavior is balanced by the considered additional variables (respect to the input indices) of the hydrologic cycle.

In the following Table 5.V have been summarized all the characterization parameters of detected droughts by indices for some of the aggregation time scales.

The parameters calculated as defined above in the paragraph 2.3 are:

- ✓ number of detected run of drought;
- ✓ duration;
- ✓ Minimum, maximum and mean values of the drought index;
- ✓ Cumulative deficit over the drought interval;
- ✓ Magnitude of the drought event.

Table 5.V - Characterization parameters of droughts detected by indices

	PHDI	SPI (K=12)	SSI (k=9)	SPI (K=36)	SSI (K=36)
N° Droughts	27.00	21.00	27.00	11.00	7.00
Lmax	25.00	30.00	23.00	52.00	62.00
Lmean	7.30	11.43	6.15	21.45	29.86
Min index Value	-5.41	-2.67	-2.61	-2.67	-2.60
Mean index value	-2.12	-0.79	-1.04	-0.81	-0.91
Max index value	-1.00	0.00	-0.51	-0.01	-0.07
Max Cumulative Deficit	-1.02	-0.14	-0.51	-0.10	-0.89
Min Cumulative Deficit	-83.61	-37.00	-39.78	-63.39	-67.78
Mean Cumulative Deficit	-15.46	-9.06	-5.47	-14.37	-27.22
Magnitude max	-1.02	-0.05	-0.04	-0.02	-0.20
Magnitude min	-3.64	-1.42	-1.73	-1.22	-1.44
Magnitude media	-1.70	-0.60	-0.78	-0.47	-0.75
Months mild droughts	106.00	171.00	145.00	157.00	142.00
Months moderate droughts	61.00	41.00	13.00	49.00	51.00
Months severe droughts	20	18	8	16	4
Months extreme droughts	10	10	0	10	12

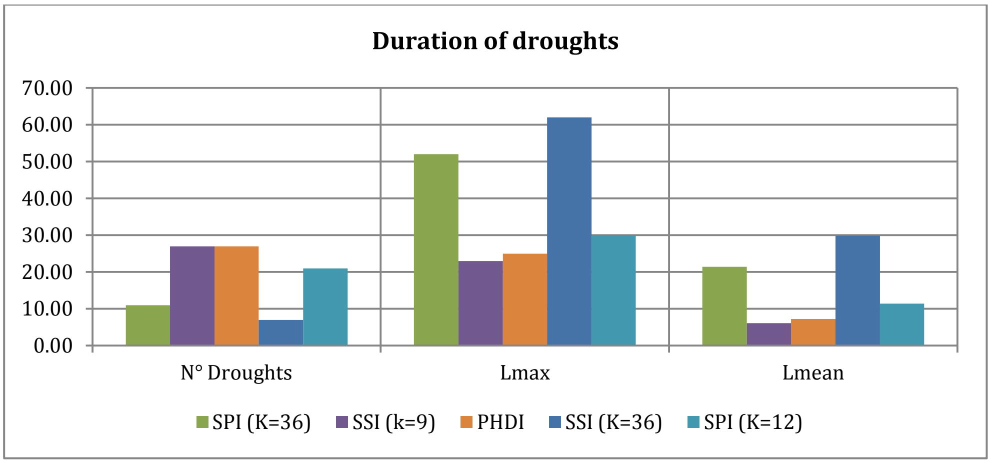

Figure 5.8 – Representation of some parameters of droughts detected by indices

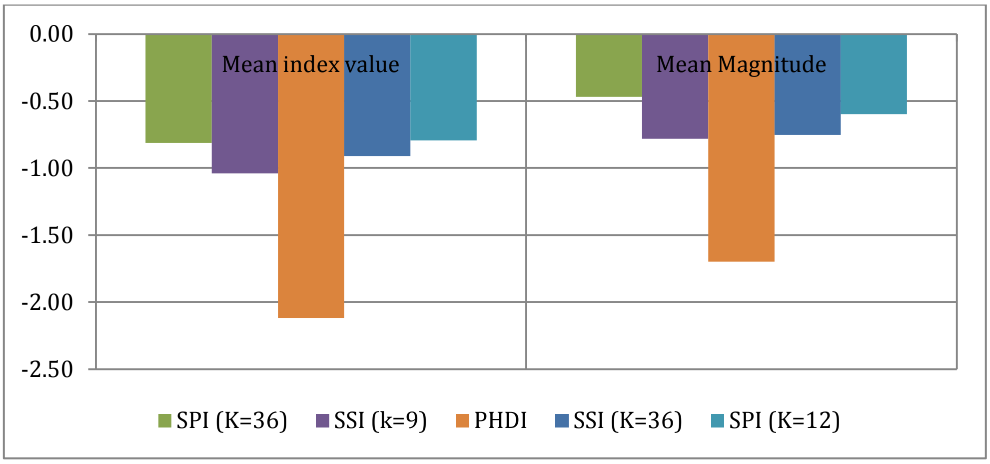

Figure 5.9 - Representation of some parameters of droughts detected by indices

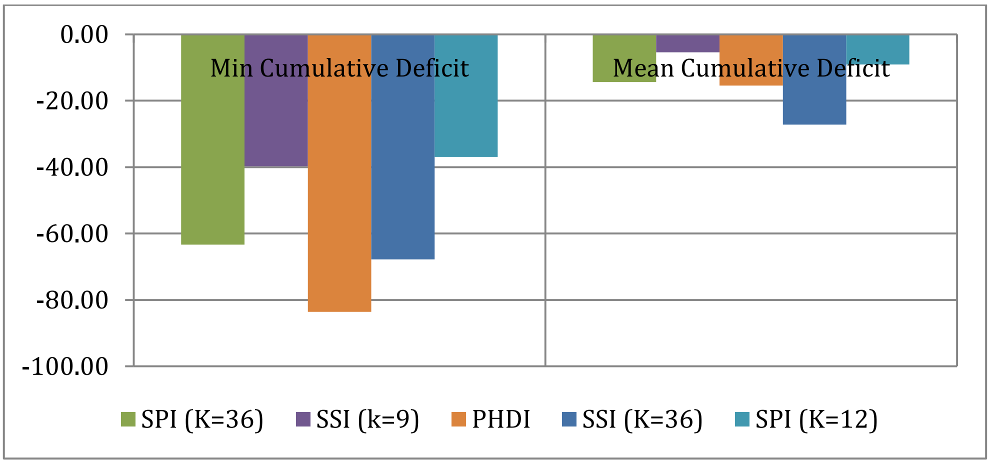

Figure 5.10 – Representation of some parameters of droughts detected by indices

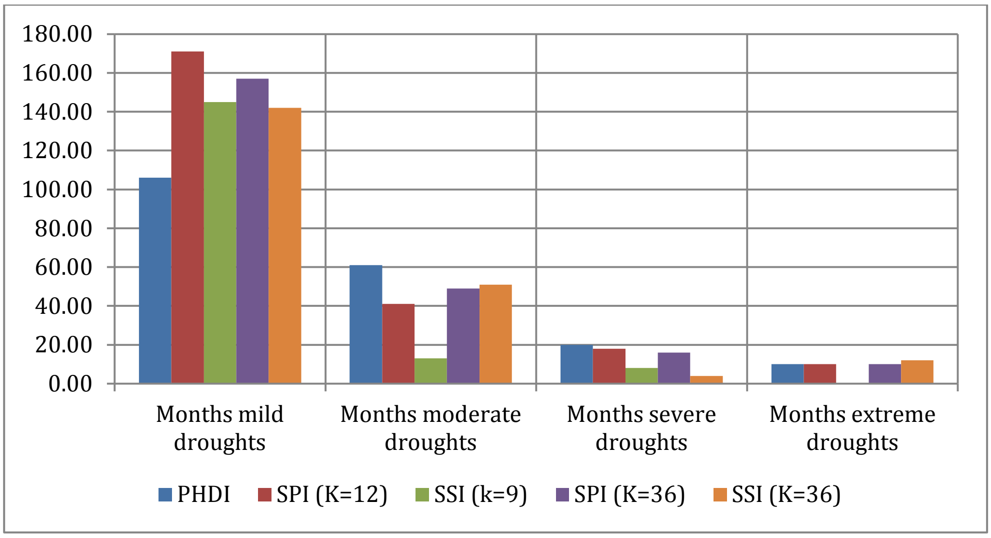

Figure 5.11 – Number of months of drought assigned by class

5.4 Concordance analysis of detected drought periods

The objective of concordance analysis is to evaluate the classification of drought severity assigned by SPI and SSI indices.

For each assessment, the matrix reports the number of time steps allocated in a classification arrangement determined by the two methods. The categorization assigned by first method (SSI) is entered in rows *i*, while the one assigned by second method (SPI) is entered in the columns j. The generic element $O_{i,j}$ of the matrix identifies the numbers of time steps to which has been assigned the class "*i*" from SSI and the class *"j"* by SPI.

Table 5.VI – Contingency table related to drought classification assigned at each time step by SSI index (in rows) and SPI index (in columns)

Drought class assigned by SPI index (k18)

	Class		0	1	2	3	4
		N	237	157	49	16	10
Drought class assigned by SSI index (k9)	0	260	202	57	1	0	0
	1	142	25	81	31	4	1
	2	51	10	18	14	8	1
	3	4	0	1	2	1	0
	4	12	0	0	1	3	8

The matrix is four by four according to the number of drought classes settled by two methods: mild, moderate, severe, extreme drought.

In the main diagonal there are records of time steps to which both methods assigned the same classification. In the others diagonals there are records of steps to which drought classification between methods has been different. The sum of diagonal (different form the main) provides the mismatching frequency in class allocation or rather the distance frequency among allocation classes. This is clarified in the following histogram in the Figure 5.12

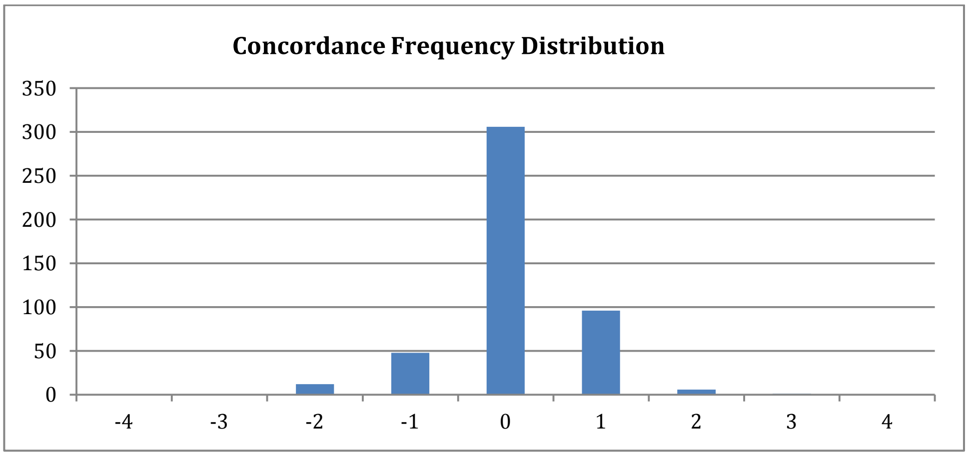

Figure 5.12 – Concordance frequency distribution in drought class allocation

The evaluation of subsistence of concordance, at fixed level of statistical relevance, has been carried out by means of the Kendall test τ_b.

The test has been applied to the contingency table removing the first row and column; the result of the test is positive with a confidence interval of 95% because is verified the condition $Z_s > Z_{s\ crit}$:

$$\tau_b = 0.627 \qquad Z_s = 15.1 \qquad Z_{s\ crit} = 1.96$$

The SSI and SPI index assign, for each interval, a drought classification with a very high level of concordance; this is evident from matrices and histograms and is confirmed by the τ_b test which is passed.

CHAPTER 6

6 CASE STUDY: APPLICATION OF AN AGGREGATE INDICATOR TO THE ACATE RIVER WATERSHED

6.1 Introduction

In this chapter, the discussed new drought monitoring product has been elaborated applying at the Acate River basin the methodology concerning the blend of indices in a single drought indicator.

The SPI, SSI and PHDI indices have been involved in order to achieve this objective.

Applicability and understanding of the indicator behavior has been carried out through a sensitivity analysis as well as investigation of trends and concordance with other drought indices.

6.2 Operational computation of ADI

As illustrated above in the paper, PCA was adopted as numerical approach to condense the essential hydrologic information from the input data set. The correlation matrices are used in order to calculate the Principal Components (PCs) that lead to define ADI time series, which is the normalized first PC because it explains the largest fraction of the variance described by the full standardized data set. The first PC is deseasonalized by his standard deviation to enable each month's ADI to represent a normalized expression of variability.

Computation of ADI can be readily accomplished using statistical/mathematical software: in this research the ADI was calculated using code written for MATLAB.

Due to the nine aggregation scales in which SPI and SSI indices were computed (PHDI has a fixed time scale) and the large amount of data, several combination of monthly time series of ADI (derived from indices at different scale) have been considered.

Considering all 12 months, PC1 was able to describe in all combinations a good percentage of the data set variance and in any case less than 60% (as shown in following Figure 6.1and Figure 6.2).

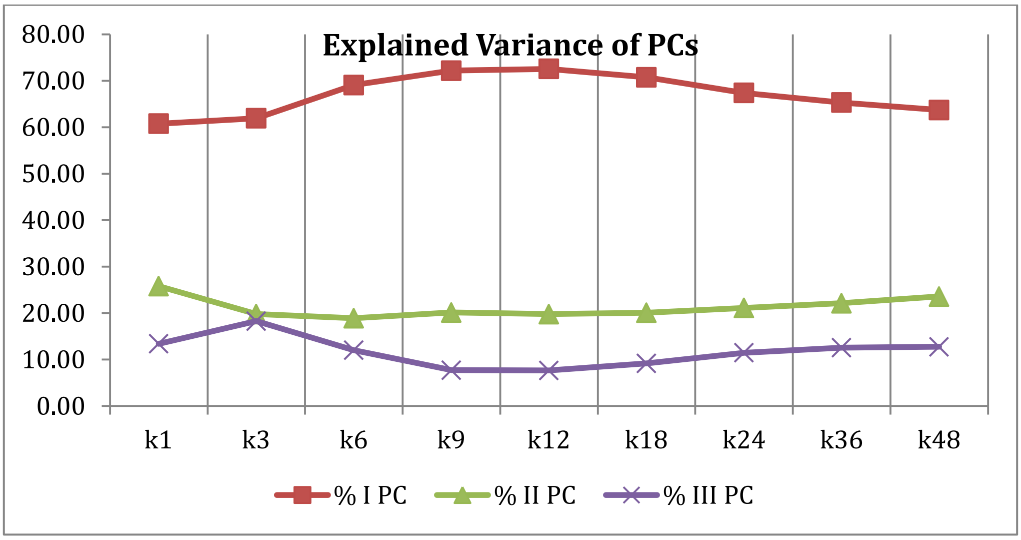

Figure 6.1 – Explained variance of first three PC in case of same k-value of aggregation time scale of SPI and SSI indices

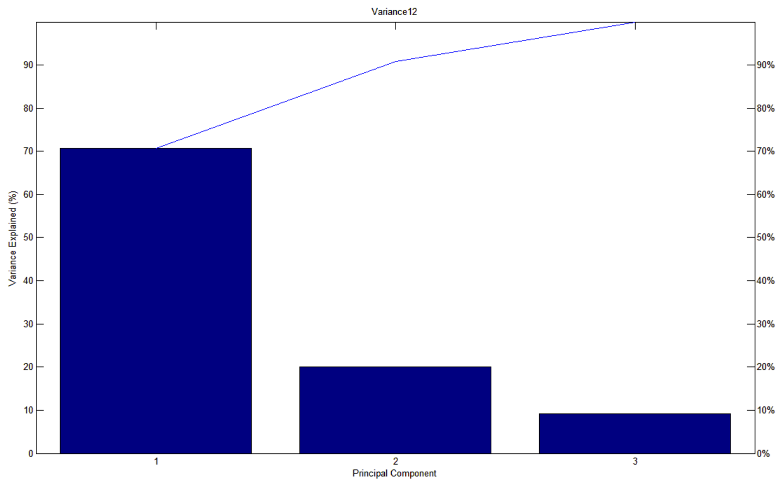

Figure 6.2 - Explained variance in case of k=12

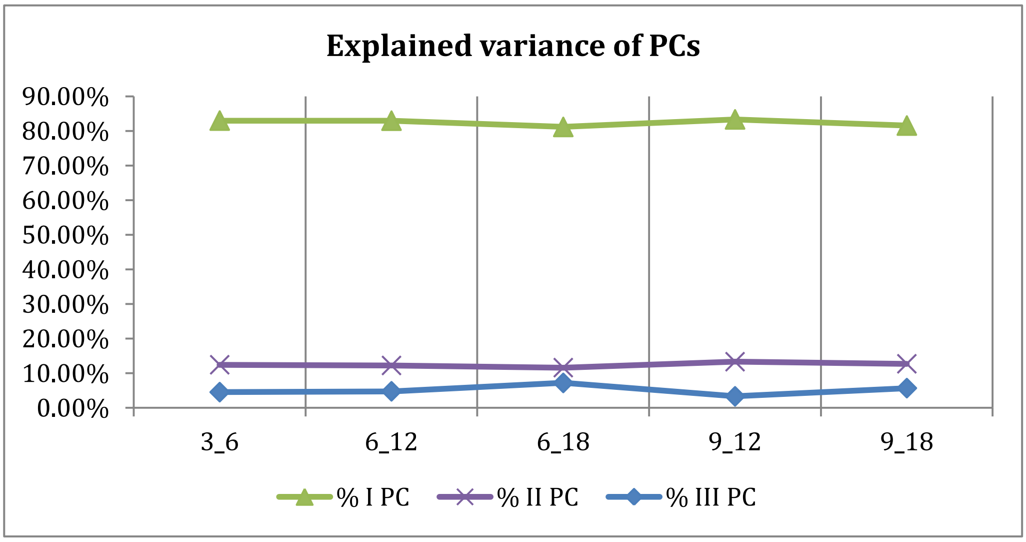

Figure 6.3 – Explained variance in case of combined k-value of aggregation time scale of (correspondingly) SSI and SPI indices.

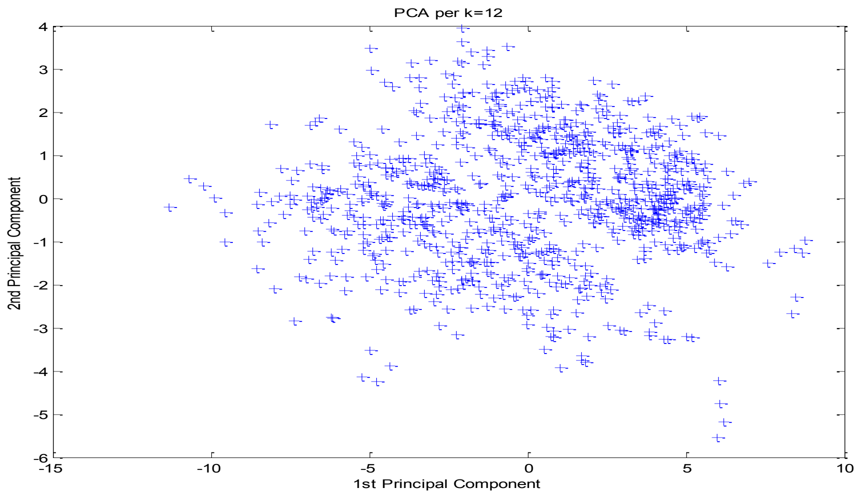

Figure 6.4 – By way of example PC1 e PC2 are represented, showing that are orthogonal vectors thus completely independent.

As results of PCA, loadings are obtained or rather the coefficients of the principal component analysis that have the significance of respectively weights of original indices. In follow table 6.I and Figure 6.5 are specified loadings at each time scale for the PC1: it is evident that weights are equally distributed over indices.

Table 6.I – Coefficients of first principal component.

I PC	k1	k3	k6	k9	k12	k18	k24	36	k48
SPI	29.7%	34.6%	35.4%	35.5%	35.1%	34.5%	34.2%	33.4%	32.7%
PHDI	35.3%	34.4%	35.3%	34.9%	35.1%	35.8%	35.3%	34.9%	35.9%
SSI	35.0%	31.2%	29.3%	29.5%	29.9%	29.7%	30.5%	31.7%	31.4%

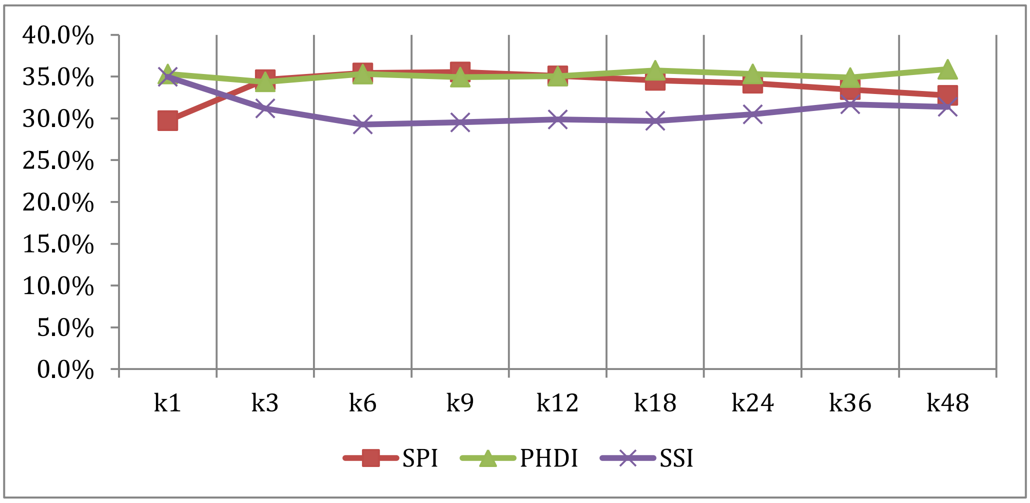

Figure 6.5 – Representation of PC1 coefficients at different time scale.

The time series of the developed ADI for the Acate River catchment is shown in Figure 6.6.

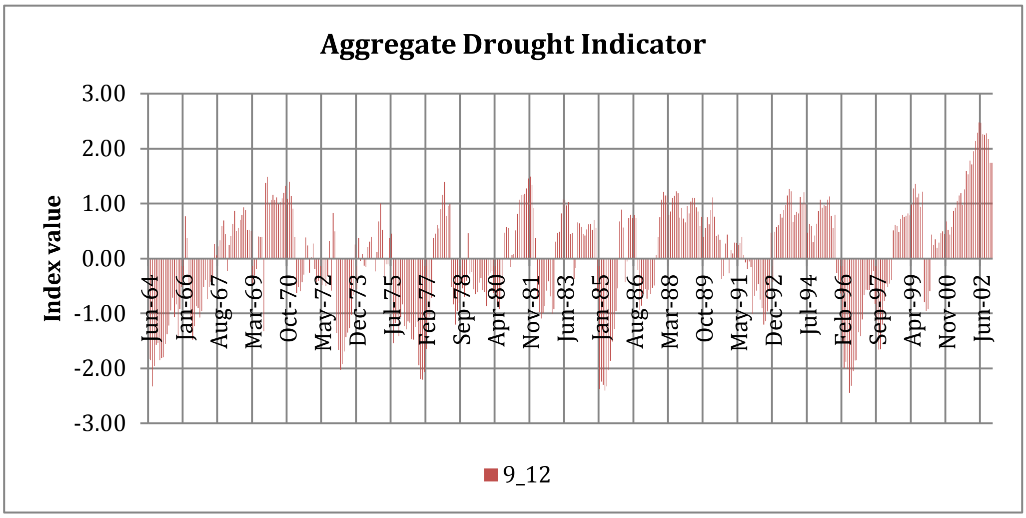

Figure 6.6 – ADI time series derived from PHDI, SPI (k=12) and SSI (k=9)

Table 6.II – Characterizing parameters of droughts detected by ADI and assigned drought classes

ADI

	Drought duration T (months)	$\sum T_k$ "Cumulative Index"				**Mild**	**Moderate**	**Severe**	**Extreme**
			Min_k	$\sum T_k$**/T "Magnitude"**		0.0	-1.0	-1.5	-2.0
number	27					32	7	1	0
Min	1	-39.78	-2.61	-1.73		1	1	1	0
Mean	6.15	-5.47	-1.04	-0.78					
Max	23.00	-0.51	-0.51	-0.04		14	4	8	0
Total	166	-147.6				145.0	13.0	8.0	0.0

Observing the chart in the Figure 6.6, the indicator ADI was delightfully able to detect droughts at different levels of severity as well as most common indices in the 40 years from 1963 to 2002; in effect, with a qualitative check of plotted time series, droughts of 1981-82, 1988-91, 1994-95, 1999-2002 are identified. A quantitative analysis has to be carried out in order to classify droughts characteristics as length, cumulative deficit and intensity.

6.3 Comparison of characteristics of detected drought periods

A qualitative and quantitative comparison, between characteristics of identified droughts, has been made referring to introduced indices.

Observing the graph of PHDI and SPI, they visibly agree in classifying drought circumstances in despite that classes are settled following different parameters; further, considering the SPI index at the aggregation scale k=12, it generally reveal values halved respect to the PHDI index that instead classify droughts in a more severe manner.

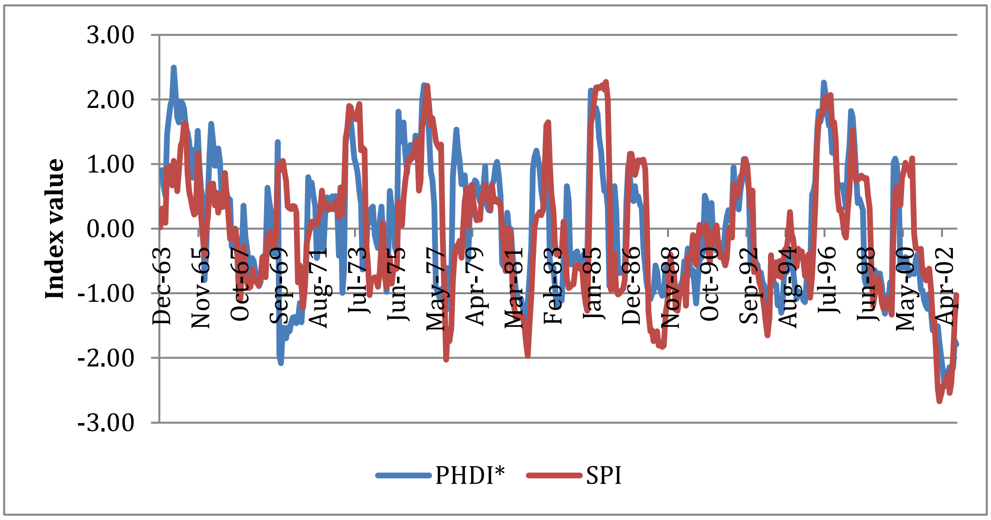

Figure 6.7 – Comparison between the SPI (k=12) and the normalized PHDI*.

As previously reported, SSI has a high concordance with the SPI; the aggregate drought indicator delineates his trace in the midway and his behavior is balanced by the considered additional variables (respect to the input indices) of the hydrologic cycle.

Looking at the chart (**Errore. L'origine riferimento non è stata trovata.**) it is evident as the ADI identify all droughts identified by the SPI, with the advantage to be more stable with smoothed peaks and detecting longer droughts characterized by lower intensity.

The same effect can be observed in the **Errore. L'origine riferimento non è stata trovata.**, comparing the ADI with the PHDI that reaches often extreme values of the index.

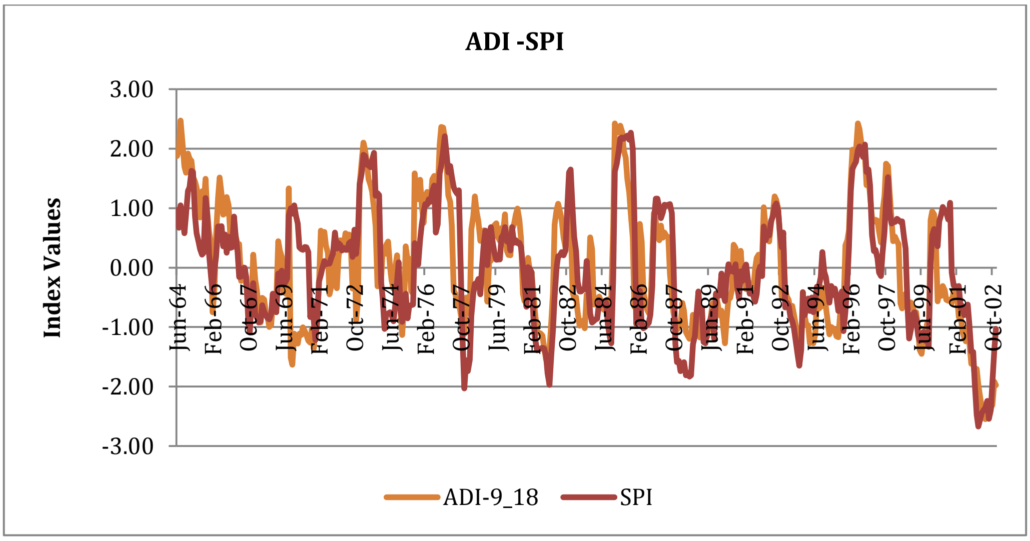

Figure 6.8 - Comparison between the SPI (k=12) and ADI, computed with PHDI, SSI (k=9) and SPI (k=18)

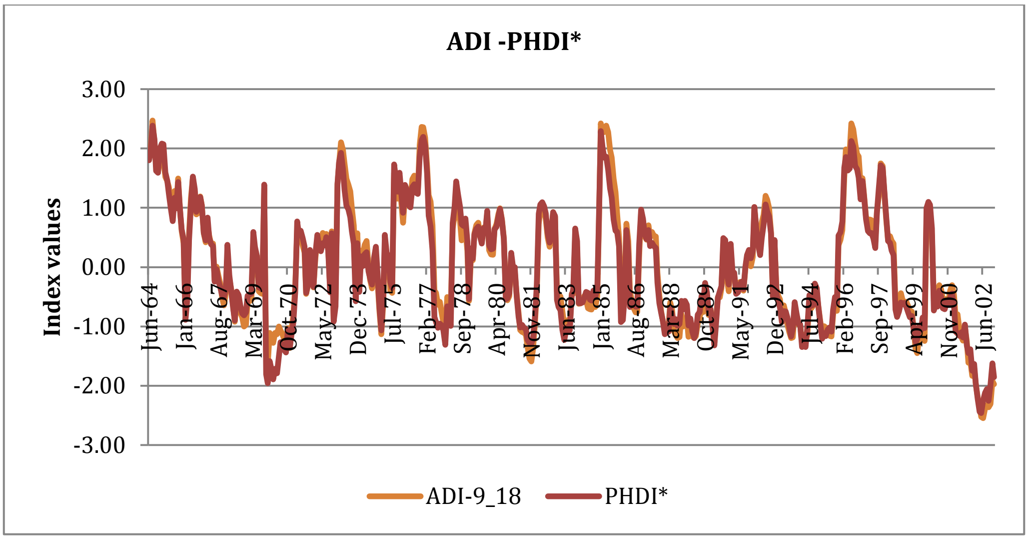

Figure 6.9 - Comparison between normalized PHDI* and ADI

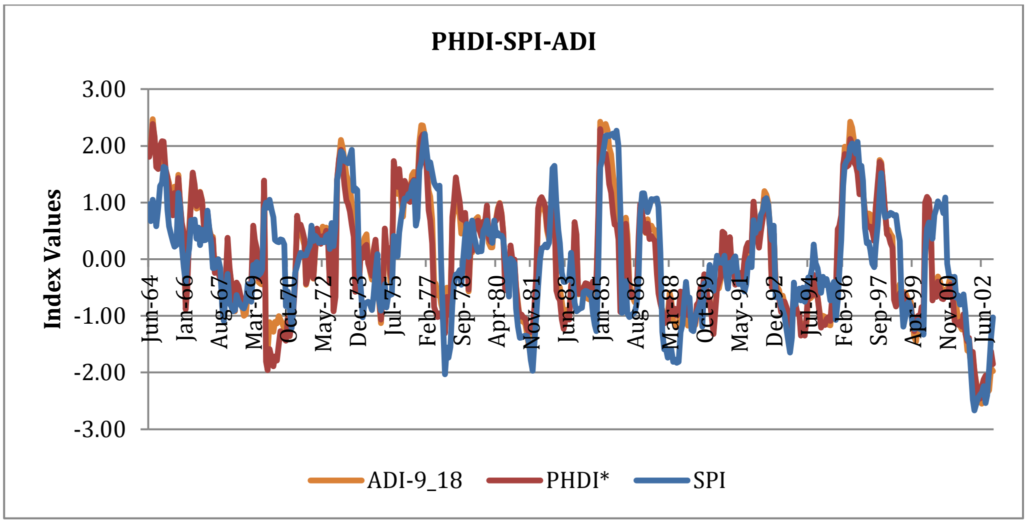

Figure 6.10 - Comparison of indices SPI, PHDI and ADI

In the following tables are summarized statistic parameters of drought periods identified by indices with classification of drought severity and respective elaboration of length, cumulative deficit and intensity.

Table 6.III - -Summarizing table of main drought parameters of identified droughts

	PHDI	SPI (K=12)	SSI (k=9)	SPI (K=36)	SSI (K=36)	ADI (k1=9, K2=18)
N° Droughts	27.00	21.00	27.00	11.00	7.00	28.00
Lmax	25.00	30.00	23.00	52.00	62.00	23.00
Lmean	7.30	11.43	6.15	21.45	29.86	5.75
Min index Value	-5.41	-2.67	-2.61	-2.67	-2.60	-2.27
Mean index value	-2.12	-0.79	-1.04	-0.81	-0.91	-0.99
Max index value	-1.00	0.00	-0.51	-0.01	-0.07	-0.51
Max Cumulative Deficit	-1.02	-0.14	-0.51	-0.10	-0.89	-0.51
Min Cumulative Deficit	-83.61	-37.00	-39.78	-63.39	-67.78	-34.70
Mean Cumulative Deficit	-15.46	-9.06	-5.47	-14.37	-27.22	-5.71
Magnitude max	-1.02	-0.05	-0.04	-0.02	-0.20	-0.51
Magnitude min	-3.64	-1.42	-1.73	-1.22	-1.44	-1.58
Magnitude media	-1.70	-0.60	-0.78	-0.47	-0.75	-0.81
Months mild droughts	106.00	171.00	145.00	157.00	142.00	145.00
Months moderate droughts	61.00	41.00	13.00	49.00	51.00	14.00
Months severe droughts	20	18	8	16	4	2.00
Months extreme droughts	10	10	0	10	12	0.00

CHAPTER 7

7 CASE STUDY: CHARACTERIZATION OF DROUGHT AREAL EXTENT IN SICILY

7.1 Introduction

Here hence is reported the application of the methodology presented above in chapter 3, concerning the probabilistic characterization of severity of drought areal extent. In order to satisfy this purpose SPI index has been taken as spatial drought variable and computed in each of the selected rain stations over the region of Sicily.

Drought severity-areal extent-frequency (SAF) curves were traced out associating fixed probability of event occurrence to thresholds of regional area affected by drought. In the process, the drought areal extent values were blended up to produce drought severity maps using simple tools as the geographical information system.

7.2 Probabilistic characterization of areal extent

As described above in chapter 4, available rain stations over the studied area have been previously identified: the study network consists of 105 stations with significant record of 84 years of historical time series at monthly time scale (1921 – 2005).

SPI index has been computed for each of them for several aggregation time scales (1, 3, 6, 9, 12, 18, 24, 36 e 48 months).

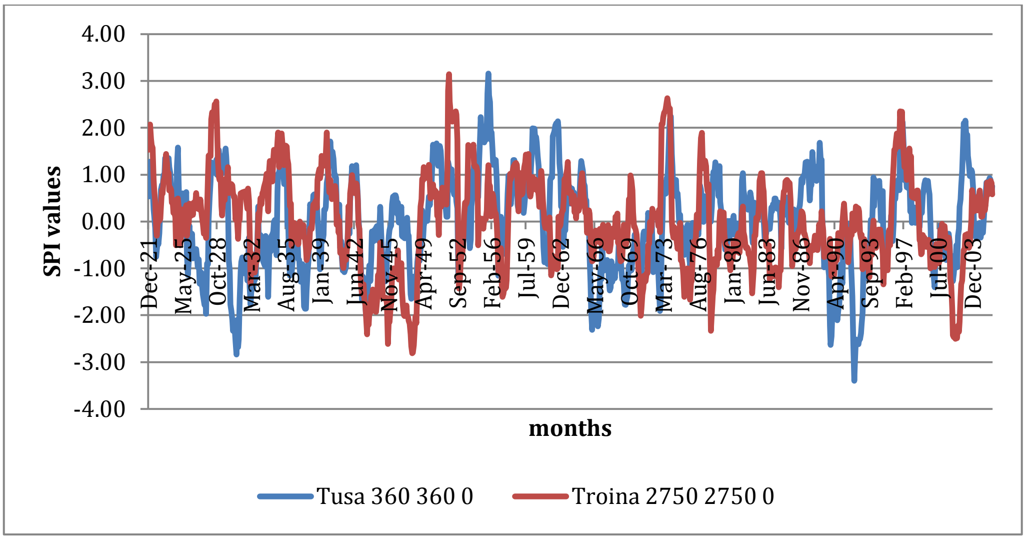

Figure 7.1 – Example of SPI time series elaborated for the rain stations of Tusa and Troina at the aggregation time scale k=12

Further, percentage of influences area a_k of each gauge station respect to the full regional area was determined as showed in following Table 7.I:

Threshold values for SPI (z_0) have been fixed and z values then compared per each station, or rather an analysis of occurrence frequency of the condition $z \leq z_0$ has been accomplished and $A(z_0)$ calculated for each aggregation time scale: $A(z_0)$ is substantially the percentage of regional area affected by a fixed level of drought therefore $SPI \leq z_{0.}$

In order to trace out the cumulative curves of areal extent of drought the couple of values a(k),z(k) have been sorted as showed in following Table 7.I

Table 7.I – Example of cumulative areas related to selected rain gauge stations for the November 1973

Nov-73				Nov-73			
Stations	SPI	Area (%)	Cumulative area	Stations	SPI	Area (%)	Cumulative area
Sciacca	-1.19	1.05%	1.1%	Trapani	0.99	1.37%	51.4%
Roccamena	-0.90	0.93%	2.0%	Messina	0.99	1.63%	53.0%
Cattolica Eraclea	-0.84	1.39%	3.4%	Augusta	1.02	0.70%	0.7%
S. Martino delle Scale	-0.74	0.96%	4.3%	Caltagirone	1.05	1.01%	1.7%
Bivona	-0.58	0.40%	4.7%	S. Cataldo	1.07	1.44%	3.1%

Continue table 7.!

Nov-73				Nov-73			
Stations	SPI	Area (%)	Cumulative area	Stations	SPI	Area (%)	Cumulative area
Menfi	-0.57	1.11%	5.8%	Pietraperzia	1.07	1.50%	4.6%
Partinico	-0.45	0.72%	6.6%	Cefalu'	1.09	1.48%	6.1%
Piano del Leone	-0.45	0.93%	7.5%	Mazzarino	1.14	0.29%	6.4%
Geraci Siculo	-0.44	1.31%	8.8%	Mussomeli	1.28	1.20%	7.6%
Ciavolo (contrada)	-0.43	1.15%	10.0%	Caltanissetta	1.34	2.15%	9.8%
Calatafimi	-0.36	1.07%	11.0%	Palermo (p.zza Verdi)	1.35	0.86%	10.6%
Sambuca di Sicilia	-0.36	0.73%	11.8%	Villarosa	1.39	0.47%	11.1%
Ragusa	-0.34	0.61%	12.4%	Ciminna	1.49	0.45%	11.6%
Fastaia	-0.17	1.73%	14.1%	S. Cristina Gela	1.54	0.71%	12.3%
Caltabellotta	-0.17	0.66%	14.8%	Cerami	1.54	1.38%	13.6%
Castelvetrano	-0.11	1.32%	16.1%	Lercara Friddi	1.58	1.28%	14.9%
Racalmuto	-0.01	0.53%	16.6%	Mirabella Imbaccari	1.60	0.92%	15.8%
S. Vito Lo Capo	0.00	0.91%	17.5%	Canicattini Bagni	1.64	2.00%	17.9%
Ispica	0.04	0.33%	17.9%	Ramacca	1.64	0.69%	18.5%
Agrigento	0.05	0.39%	18.2%	Francofonte	1.65	1.19%	19.7%
Specchia	0.06	1.11%	19.4%	Lentini (citta')	1.66	1.06%	20.8%
Corleone	0.09	1.04%	20.4%	Mineo	1.68	0.84%	21.6%
Campofelice di Fitalia	0.14	1.53%	21.9%	S. Caterina Villarmosa	1.70	0.58%	22.2%
Ribera	0.17	0.72%	22.6%	Canicatti'	1.77	1.67%	23.9%
Modica	0.18	0.18%	22.8%	Scillato	1.78	1.23%	25.1%
Siracusa	0.25	0.78%	23.6%	Licata	1.78	0.67%	25.8%
Palazzo Adriano	0.27	1.10%	24.7%	Linguaglossa	1.91	0.58%	26.4%
Partanna	0.30	0.74%	25.4%	Tripi	1.96	0.58%	27.0%
Diga Maganoce	0.38	1.05%	26.5%	Paterno'	1.96	0.64%	27.6%
Alimena	0.38	1.38%	27.9%	Tortorici	2.00	0.55%	28.2%
S. Giuseppe Jato	0.40	0.62%	28.5%	Cesaro'	2.03	0.68%	28.8%
Alcamo	0.40	1.70%	30.2%	Mistretta	2.06	1.13%	30.0%
Marianopoli	0.40	1.46%	31.6%	Castelbuono	2.06	0.31%	30.3%
S. Biagio Platani	0.40	0.44%	32.1%	Bronte	2.06	0.75%	31.0%
Ganzirri	0.47	0.93%	33.0%	Capizzi	2.07	1.24%	32.2%
Marsala	0.49	1.00%	34.0%	Piazza Armerina	2.13	1.01%	33.3%
Scicli	0.50	1.13%	35.1%	Petralia Sottana	2.14	1.04%	34.3%
S.Stefano di Briga	0.52	1.23%	36.4%	S. Fratello	2.17	1.05%	35.3%
Pioppo (villa)	0.54	0.73%	37.1%	Tusa	2.18	2.03%	37.4%
Butera	0.62	1.53%	38.6%	Zafferana	2.28	1.14%	38.5%
Chiramonte Gulfi	0.65	0.45%	39.1%	Caronia	2.35	0.97%	39.5%
Caccamo	0.68	1.02%	40.1%	Troina	2.41	0.46%	39.9%
Enna	0.72	1.21%	41.3%	Castel di Judica	2.53	0.39%	40.3%

Continue table 7.!

Nov-73				Nov-73			
Stations	SPI	Area (%)	Cumulative area	Stations	SPI	Area (%)	Cumulative area
Gela	0.73	1.08%	42.4%	Vallelunga	2.56	0.77%	41.1%
Cinisi	0.74	0.75%	43.1%	Castroreale	2.74	0.66%	41.8%
Vicari	0.85	0.66%	43.8%	Catenanuova	2.81	0.35%	42.1%
Sommatino	0.89	0.64%	44.4%	Francavilla di Sicilia	2.95	1.30%	43.4%
Mazara del Vallo	0.92	0.78%	45.2%	Nicosia	3.02	0.65%	44.1%
Palazzolo Acreide	0.94	1.20%	46.4%	Floresta	3.12	0.51%	44.6%
Catania	0.94	0.63%	47.1%	Montalbano Elicona	3.53	0.90%	45.5%
Vittoria	0.95	1.13%	48.2%	Antillo	3.59	0.47%	46.0%
Marineo	0.96	0.70%	48.9%	Nicolosi	4.10	1.00%	47.0%
Acireale	0.98	1.17%	50.0%				

As an illustrative, yet incomplete example, in following Figure 7.2 some of mentioned curves are outlined for the month of November in the years 1973, 1989, 2003.

Chosen curves show the difference among samples of dry, normal and wet months.

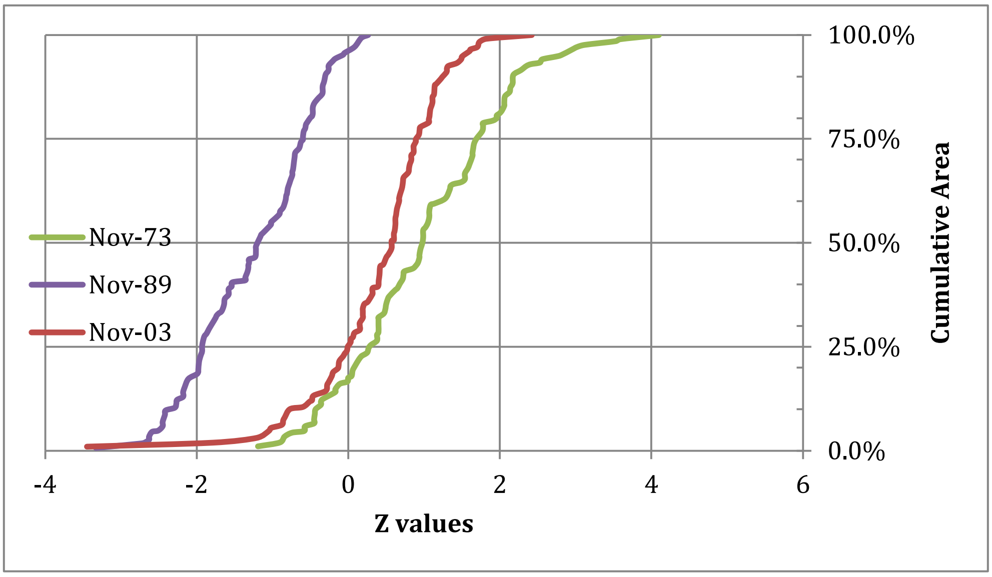

Figure 7.2 – Cumulative area affected by drought for some year in November

Effectively, as confirmed by the curve referring to November 1973, the 1989 was a dry year with nearly 100% of the regional area of Sicily involved in a water deficiency condition and almost the 50% in quite severe circumstance of drought.

More than thousand analogous curves, for every month of the analysis, have been traced out. In following Figure 7.3 is shown a more explicating example: in the left side of the figure have been selected curves referring to high values of regional area involved in drought condition while in the right side it is possible to observe the difference amid quite wet condition spread in the region.

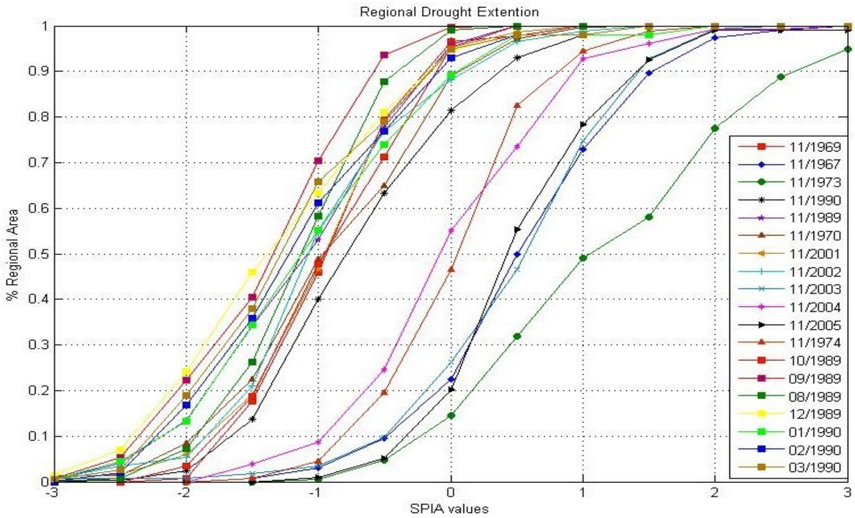

Figure 7.3 – Cumulative area affected by drought for some years

As it is possible to notice, settled curves point out clearly the existence and severity of drought events: a measure of his extent and spatial variability has been thus introduced.

SAF curves indicate variability of drought extent and severity by means of variability of them gradient: the less a chosen curve is inclined the less are the numbers of drought classes for which the regional area is involved denoting certain homogeneity of drought condition within the whole area under study and viceversa.

Furthermore as reminded in the SPI description, varying the aggregation time scale also the typology of observed drought changes: in this point of view SAF curves are helpful to investigate variability of drought characteristics.

In order to graphically check spatial patterns of drought the SFA curves were elaborated over the region of Sicily comparing maps of drought events occurred in different years. The geographical information system was helpful to produce drought maps by means of interpolation of SPI values previously calculated per each rain station following the calculate-interpolate criterion.

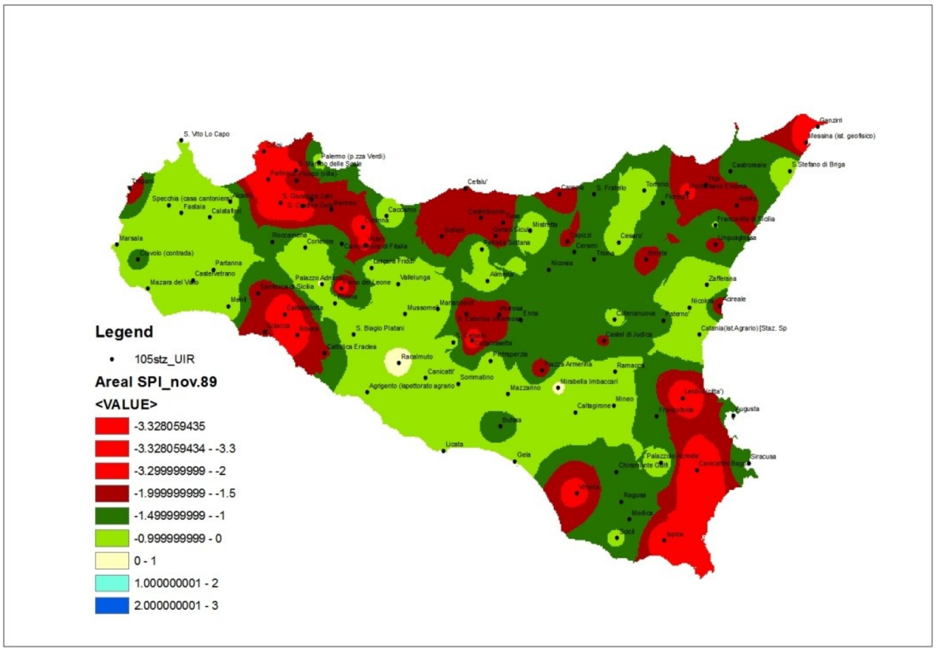

Figure 7.4 – Map of drought condition in Sicily detected trough SPI index in November 1989

Interpolation was arranged pursuing two different methods: the deterministic local method (inverse distance weighting) and the geostatistical one (universal and ordinary kriging): the standardized precipitation index was considered as a drought variable and the Inverse Distance Weighting (IDW) approach was selected for the spatial interpolation of z values in a fixed month over the Sicily region. In the Figure 7.4 is shown the map related to the November 1989 (where are evident the serious and spread drought condition all over the region of Sicily) while in following maps Figure 7.5 is possible to compare the difference about spatial distribution of drought in a relative wet year as the November 2003

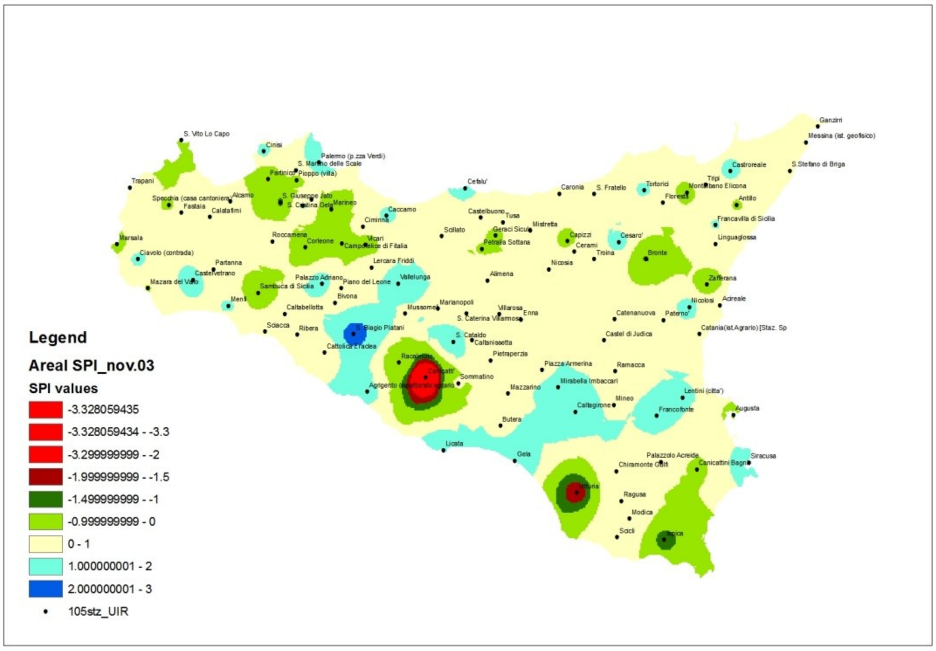

Figure 7.5 - – Map of drought condition in Sicily detected trough SPI index in November 2003

Afterward, fixing critical drought area threshold (e.g. 5%, 25%, 50%, 75%, 99%), per each month of the historical time series and for each station the a_k values have been associated the corresponding value of z_k previously sorted in a crescent way; with this approach SPI values corresponding to such threshold of critical area were detected.

Generated SPI (a_k) series were examined to carry out a frequency analysis in order to estimate the matching probability of occurrence and return period of drought events that involve a predetermined threshold of regional area.

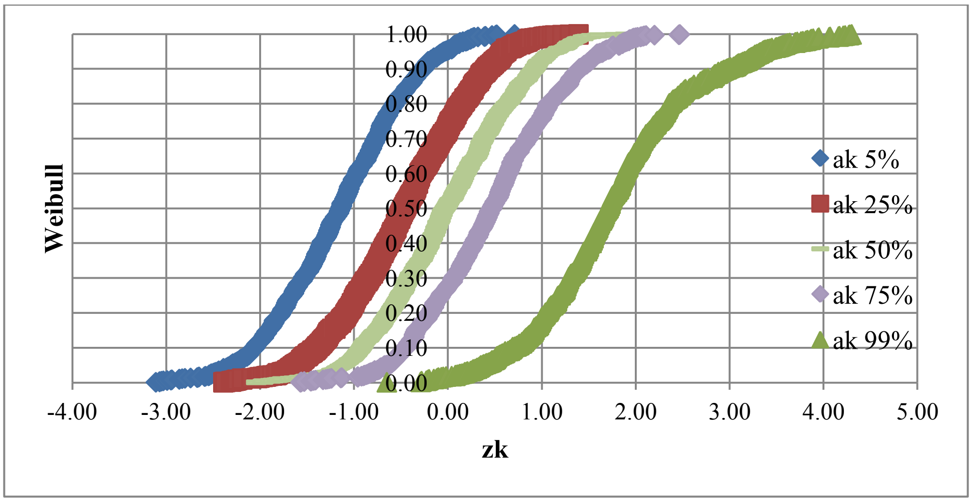

Figure 7.6 – Frequency analysis of SPI values corresponding to fixed thresholds of regional area

The severity drought values were fitted with Normal and Lognormal probability distributions. The normal distribution was selected for frequency analysis, as it passed the Chi-Square tests for SPI series.

Thus drought severity area frequency and probability curves have been traced out; once fixed values of investigated probability of occurrence, the area involved in some drought events can be estimated by means of the illustrated relationship.

Effectively in following Figure 7.7 are traced out the observed frequency curves related to cited sample months (November 1973-1989-2003) and, besides, are traced out the curves of fixed probability of occurrence.

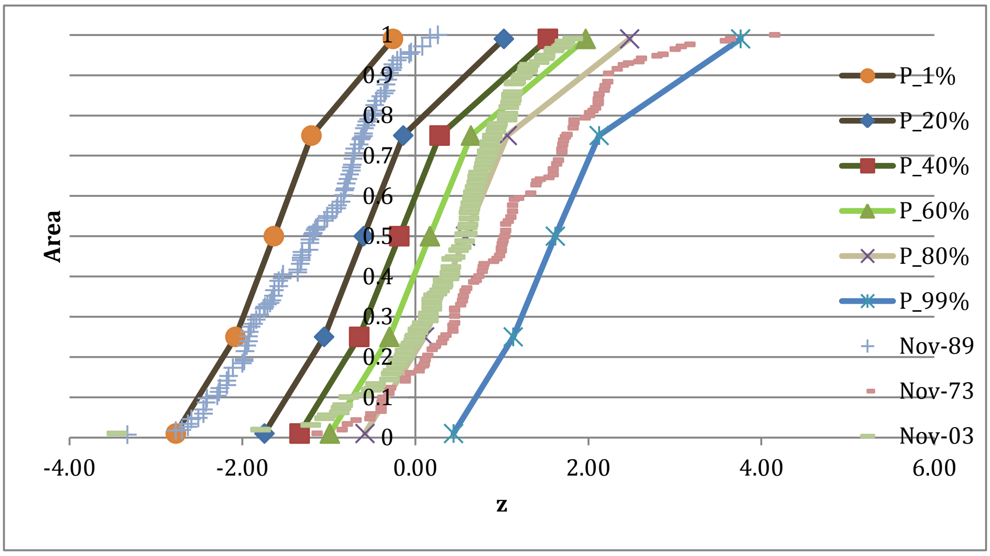

Figure 7.7 – SPI values corresponding to percentage of regional area once fixed critical probability threshold

Substantially it is possible to read from the chart the probability that a fixed percentage of regional area is affected by a certain level of drought.

For example, from the Figure 7.7, the probability that 50% of the area is affected by mild drought is of the 40% while the probability that the 25% of regional area is affected by the same drought is of 20%.

The graphic information confirms that drought occurred in November 1989 was really an extreme event whit a probability of occurrence close to 1% while the other two considered years are quite normal condition with occurrence probability ranging from 60% to 99%. The viceversa of this reasoning is shown in Figure 7.8, where this time percentage of regional area is fixed. Even this time it is interesting to notice how the frequency curve related to nov-89 imitate quite exactly the curve of 5% of area.

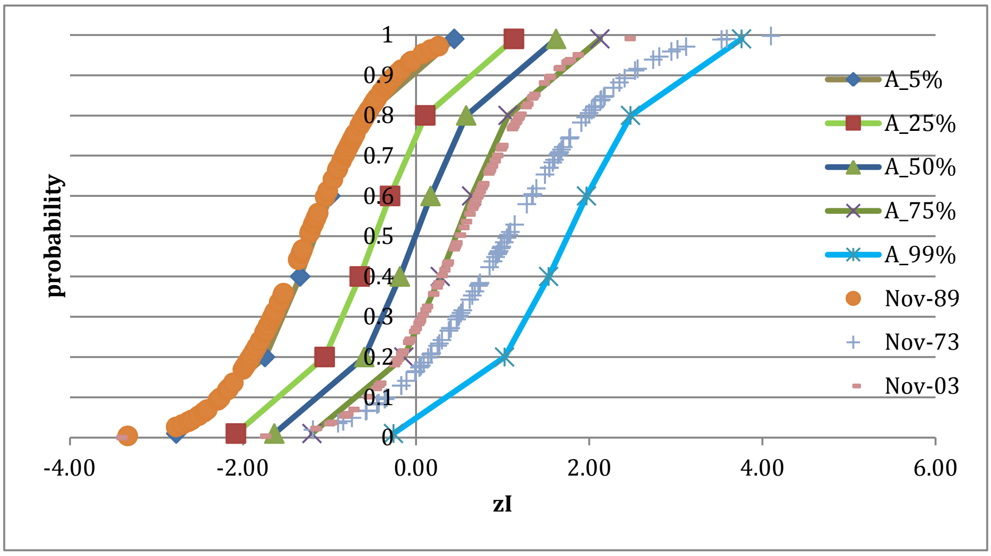

Figure 7.8 - SPI values corresponding to some probability values once fixed critical area threshold

It means that the area that was involved in such drought event with such z values has the same probabilities of occurrence related to just the 5% of regional area.

CHAPTER 8

8 CONCLUSIONS

It is largely recognized that drought monitoring is one of the essential elements for an improved management of water resources, both at river basin or water supply system scale, as well over a wider region.

Several drought indices have been developed in last decades and still new ones are being proposed: they generally refer to some particular typology of drought focusing alternatively on meteorological, hydrological or agricultural aspects.

Despite the efforts, the multivariate nature of drought still poses some questions related to its monitoring with reference to the choice of the most appropriate indices. Also the need to develop indices able to grasp different aspects, such as meteorological and hydrological at river basin scale as well as spatial extension at regional scale, arises in order to simplify the information flow with politicians and decision makers.

The present thesis has addressed some of the above issue, attempting to contribute to a better drought monitoring at river basin and regional scale.

As first step, a methodology of analysis and comparison of most common drought indices has been applied. More specifically, a comparison between the Standardized Precipitation Index, the Standardized Streamflow Index, and the Palmer index has been carried out with reference to the Acate River watershed, in the south of Sicily. Such comparison has revealed that the three indices present different degrees of agreement in detecting drought conditions depending on the adopted aggregation time scale. Furthermore the analysis has revealed that the SPI at a proper aggregation time scale can be representative of hydrological and agricultural droughts, thus confirming its suitability as a tool for monitoring droughts at river basin scale.

Then a methodology for the aggregation of such indices in a unique one based on Principal Component Analysis has been applied. The resulting index was able to clearly detect most of registered historical droughts; furthermore, the indirect presence of various components of the hydrologic cycle (precipitation, air temperature, streamflow) let the indicator have a lower sensitivity to the variability of a single hydrologic variable. The main advantage of the proposed aggregated index is that it integrates in a single value different information related to meteorological, hydrological, and agricultural droughts.

A methodology for the probabilistic characterization of drought areal extent based on SPI has been developed as a tool to support drought monitoring at regional scale. It consists in the estimation of the measure of drought severity associated with different areal extents (in terms of percentage area of the investigated region). Then a probability distribution has been fitted to drought severity series for different areal extents and drought Severity Area Frequency curves for the region of Sicily have been developed.

Comparison of the developed SAF curves with severity-area curves related to historical droughts, as well as to wet periods, has indicated the feasibility of the developed tool, both to characterize past droughts, as well as to probabilistically assess the magnitude of an ongoing drought for monitoring purposes.

The overall conclusion of the thesis is that, although different indices are required to properly monitor drought at river basin scale, aggregation of several indices into a single one can represent an useful tool for decision makers for an overall assessment of drought conditions in a basin. Also, probabilistic assessment of drought areal extent over a large region provides important information in order to implement proper mitigation strategies able to reduce the most significant impacts of droughts.

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APPENDIX

Streamflow data

Appendix A - Streamflow reconstructed at Ragoleto dam (Mm^3)

	jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec
1963	0.65	1.18	0.87	0.84	1.00	0.61	1.02	0.19	0.32	0.17	0.06	0.99
1964	4.08	2.19	2.84	7.09	1.01	0.78	0.69	0.56	0.55	0.20	0.26	1.35
1965	3.24	3.04	1.46	0.81	0.25	0.65	0.50	0.35	0.77	1.71	0.56	0.53
1966	1.13	0.88	1.17	2.04	2.73	1.61	0.63	0.27	0.57	0.42	0.46	0.47
1967	1.55	4.03	1.30	0.79	0.36	0.71	0.30	0.07	0.67	0.00	0.25	0.58
1968	3.49	1.67	0.90	0.49	0.20	0.63	0.09	0.00	0.72	0.07	0.85	0.51
1969	1.06	0.70	2.04	0.90	0.51	0.32	0.29	0.37	13.00	8.47	0.96	2.31
1970	2.30	1.78	1.62	1.29	0.64	1.06	0.50	0.03	0.04	0.25	0.24	0.63
1971	1.51	2.79	2.40	0.96	0.44	0.70	0.27	0.00	0.61	1.05	0.48	0.83
1972	1.57	2.72	4.36	1.24	0.72	0.85	0.20	0.00	0.62	0.49	0.34	2.12
1973	11.40	7.19	7.90	7.70	1.58	1.89	1.22	0.82	0.84	0.04	0.38	1.66
1974	0.58	2.00	1.62	1.09	0.58	1.20	0.63	0.49	0.87	0.51	0.64	0.67
1975	0.18	1.92	1.26	0.43	0.44	0.70	0.27	0.35	0.74	0.37	2.41	1.27
1976	1.89	6.13	3.47	1.51	0.94	1.34	0.65	0.09	0.53	2.81	8.42	7.00
1977	5.16	5.78	1.09	1.12	0.63	1.60	0.91	0.41	0.96	0.89	0.42	0.41
1978	0.55	0.44	0.43	0.74	0.49	1.00	0.39	0.00	0.10	0.43	0.76	0.96
1979	0.99	1.95	2.36	1.02	0.62	0.80	0.17	0.00	0.18	0.12	0.70	0.58
1980	1.40	1.38	2.32	1.25	0.67	1.02	0.24	0.00	0.36	0.00	0.41	0.55
1981	0.73	0.66	0.66	0.36	0.06	0.68	0.17	0.07	0.53	0.30	0.35	0.56
1982	4.95	3.93	3.61	1.58	0.83	0.15	0.96	0.00	0.24	0.38	1.44	2.21
1983	2.32	0.64	0.72	0.41	0.04	0.53	0.18	0.00	0.44	0.25	0.74	1.47
1984	0.67	1.00	0.94	0.67	0.05	0.55	0.34	0.00	0.74	0.00	5.80	0.51
1985	42.23	15.57	2.33	2.75	1.10	1.10	0.72	0.00	0.20	0.00	0.40	0.26
1986	0.24	0.66	0.99	0.09	0.00	0.23	0.25	0.11	0.53	0.46	7.37	3.56
1987	2.67	1.96	0.82	0.88	0.90	0.71	0.51	0.25	0.41	0.00	0.14	0.27
1988	0.25	0.20	0.49	0.19	0.03	0.00	0.00	0.11	0.10	0.08	0.39	0.61
1989	0.75	1.83	0.41	0.17	0.08	0.12	0.04	0.04	0.08	0.14	0.21	0.93
1990	2.35	0.79	0.46	0.44	0.43	0.11	0.14	0.18	0.00	0.22	0.76	2.71
1991	2.48	2.34	1.62	1.06	0.50	0.30	0.14	0.18	0.42	0.21	0.24	2.29
1992	18.90	3.33	1.05	0.71	0.88	0.00	0.82	0.78	0.46	0.43	0.29	1.41
1993	1.11	0.57	1.08	0.49	0.62	0.18	0.02	0.21	0.07	0.25	1.07	3.47
1994	2.41	1.61	0.81	0.57	0.48	0.22	0.18	0.19	0.20	0.36	0.38	0.53
1995	0.85	0.57	0.48	0.35	0.27	0.17	0.07	0.00	0.37	0.17	0.60	2.21
1996	4.85	9.79	18.68	1.94	1.09	0.99	1.03	0.38	0.14	0.57	0.46	1.98
1997	2.27	1.27	1.38	0.78	0.65	0.21	0.06	0.17	0.23	2.11	3.35	2.47
1998	1.77	2.40	0.93	0.84	0.78	0.79	0.09	0.14	0.15	0.18	0.28	0.38
1999	0.55	0.46	0.44	0.30	0.19	0.07	0.05	0.06	0.58	0.19	0.83	4.63
2000	5.19	1.48	0.76	0.61	0.47	0.11	0.07	0.09	0.11	0.65	0.46	0.72
2001	3.05	1.77	1.00	0.50	0.24	0.18	0.10	0.18	0.16	0.06	0.15	0.22
2002	0.37	0.36	0.25	0.23	0.22	0.13	0.08	0.12	0.31	0.19	0.24	0.31

Appendix B Rain gauge stations involved and related percentage of influence areas

Station	Influence area	Station	Influence area	Station	Influence area
Castroreale	1.23%	Diga Maganoce	0.40%	Vittoria	2.00%
Tripi	0.64%	Corleone	0.93%	Ragusa	0.78%
Montalbano Elicona	0.86%	Roccamena	1.31%	Modica	0.68%
Tortorici	1.53%	Menfi	0.73%	Scicli	1.02%
S. Fratello	1.07%	Sambuca di Sicilia	1.08%	Ispica	2.15%
Caronia	0.66%	Caltabellotta	0.72%	Canicattini Bagni	2.03%
Mistretta	0.96%	Sciacca	0.45%	Palazzolo Acreide	1.38%
Tusa	0.61%	Piano del Leone	0.58%	Siracusa	0.67%
Geraci Siculo	0.44%	Palazzo Adriano	0.78%	Augusta	0.70%
Castelbuono	0.66%	Ribera	0.71%	Francofonte	1.28%
Cefalu'	0.47%	Bivona	0.64%	Lentini (citta')	1.67%
Scillato	1.73%	Lercara Friddi	0.75%	Cesaro'	1.05%
Vicari	0.46%	S. Cataldo	0.75%	Troina	1.05%
Campofelice di Fitalia	0.65%	S. Caterina Villarmosa	0.63%	Bronte	1.70%
Caccamo	1.17%	Marianopoli	1.04%	Nicosia	1.53%
Ciminna	0.53%	Vallelunga	1.19%	Capizzi	0.72%
Marineo	0.93%	Mussomeli	1.06%	Cerami	0.39%
Pioppo (villa)	0.29%	Racalmuto	1.15%	Paterno'	1.46%
S. Martino delle Scale	0.45%	S. Biagio Platani	1.20%	Catenanuova	1.50%
Partinico	0.58%	Cattolica Eraclea	1.13%	Castel di Judica	1.32%
Cinisi	0.35%	Agrigento	1.44%	Mirabella Imbaccari	1.00%
Palermo (p.zza Verdi)	0.77%	Canicatti'	1.30%	Caltagirone	1.63%
S. Giuseppe Jato	0.62%	Petralia Sottana	0.70%	Mineo	1.20%
Station	Influence area	Station	Influence area	Station	Influence area
Alcamo	1.01%	Alimena	1.13%	Ramacca	1.38%
Calatafimi	0.97%	Enna	1.48%	Nicolosi	0.69%
Specchia	1.11%	Villarosa	0.66%	Zafferana	0.92%
Trapani	0.58%	Caltanissetta	0.47%	Linguaglossa	1.10%
S. Vito Lo Capo	0.39%	Pietraperzia	0.90%	Acireale	0.31%
Fastaia	0.91%	Sommatino	1.23%	Catania	0.84%
Ciavolo (contrada)	1.01%	Licata	1.14%	Floresta	0.93%
Marsala	0.51%	Mazzarino	1.04%	Francavilla di Sicilia	0.73%
Mazara del Vallo	0.74%	Butera	1.37%	Antillo	1.11%
Partanna	1.13%	Gela	1.05%	S.Stefano di Briga	1.00%
Castelvetrano	1.21%	Piazza Armerina	1.24%	Messina	0.55%
S. Cristina Gela	0.33%	Chiramonte Gulfi	1.39%	Ganzirri	0.18%