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Analysis of Drought Variability in Sicily using SPI and SPEI Drought indexes

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Abstract

Monitoring drought variability is very important in the design and management of water resources systems. Over the years, many drought indexes have been used for this purpose and there is an ongoing debate in the scientific community about which of the drought indexes is more suitable, with SPI and SPEI being among the most commonly used. In this study, a comparison between the two indexes is presented by analyzing the spatial drought variability in Sicily Island. Monthly precipitation and temperature data from 50 meteorological stations covering a historical period from 1921 to 2013 were used. To compare the two indexes a Principal Components Analysis was applied to the SPI and SPEI fields. The results suggest that there is a general trend towards drier periods for the whole island and the spatial pattern characterizes Sicily uniformly. This drought pattern was captured by both indexes in a very similar way. However, differences were observed when an orthogonal varimax rotation was applied to the principal components of the two indexes. Even though, three regions of homogeneous drought conditions (southern, eastern and northern Sicily) were identified by both indexes, SPI is missing the northern region for long time scales (36 months), meaning that the incorporation of potential evapotranspiration variability in drought monitoring is crucial, at least in a local scale. A trend analysis conducted for the unrotated and rotated principal components has shown that SPEI identifies more significant trends both for the unrotated and the rotated case. Finally, the investigation of some severe drought events that occurred during the period 1980-2013 has shown that PET variability may provide some valuable additional information on the characteristics of drought events such as severity and duration but not for the onset of a drought.

Keywords: SPI, SPEI, Principal Components Analysis, drought variability, trend analysis, Sicily.

Περίληψη

Η παρακολούθηση και εκτίμηση της μεταβλητότητας των ξηρασιών αποτελεί σημαντικό κομμάτι του σχεδιασμού και της διαχείρισης συστημάτων υδατικών πόρων. Μέχρι σήμερα, διάφοροι δείκτες ξηρασίας έχουν προταθεί και χρησιμοποιηθεί γι αυτόν το σκοπό ενώ στους κόλπους της επιστημονικής κοινότητας υπάρχουν έντονες διαφωνίες για το ποιοι είναι οι αποτελεσματικότεροι. Οι δείκτες SPI και SPEI αποτελούν δύο από τους πιο συχνά χρησιμοποιημένους δείκτες. Στην παρούσα μελέτη γίνεται μια σύγκριση των δύο δεικτών αναλύοντας χωρικά την μεταβλητότητα της ξηρασίας στην νήσο Σικελία. Γι αυτόν τον σκοπό χρησιμοποιήθηκαν μηνιαία δεδομένα βροχόπτωσης και θερμοκρασίας από 50 μετεωρολογικούς σταθμούς και τα οποία καλύπτουν μια περίοδο από το 1921 μέχρι το 2013. Για την σύγκριση των δύο δεικτών διενεργήθηκε Ανάλυση Κυρίων Συνιστωσών (ΑΚΣ). Τα αποτελέσματα της ΑΚΣ έδειξαν ότι υπάρχει μια γενική τάση προς ξηρότερες περιόδους ενώ το χωρικό μοτίβο της, χαρακτηρίζει ομοιόμορφα τη Σικελία. Αυτή η τάση ήταν εμφανής στα αποτελέσματα και των δύο δεικτών, ενώ υπήρχαν πολλές ομοιότητες μεταξύ τους. Ωστόσο, διαφορές εντοπίστηκαν όταν εφαρμόστηκε περιστροφή των κύριων συνιστωσών με τη μέθοδο της μέγιστης διακύμανσης. Αν και εντοπίστηκαν, και από τους δύο δείκτες, τρείς περιοχές με ομοιογενείς συνθήκες ξηρασίας (νότια, ανατολική και βόρεια Σικελία), ο δείκτης SPI αδυνατεί να εντοπίσει το βόρειο τμήμα της Σικελίας ως περιοχή με ομοιογενείς συνθήκες ξηρασίας για μεγάλες χρονικές κλίμακες (36 μήνες). Αυτό σημαίνει ότι η ενσωμάτωση της μεταβλητότητας της δυνητικής εξατμισοδιαπνοής στην παρακολούθηση των ξηρασιών μπορεί να αποδειχθεί σημαντική, τουλάχιστον σε τοπική κλίμακα. Τα αποτελέσματα από την ανάλυση τάσεων που διεξήχθη τόσο για την περίπτωση των μη-περιστρεμμένων αλλά και περιστρεμμένων κύριων συνιστωσών έδειξε ότι οι τάσεις που βρέθηκαν με τον δείκτη SPEI είναι στατιστικά σημαντικές και για τις δύο περιπτώσεις συγκριτικά μ αυτές του δείκτη SPI. Τέλος, μια πιο λεπτομερή ανάλυση των γεγονότων ξηρασίας που συνέβησαν την περίοδο 1980-2013 έδειξε ότι η μεταβλητότητα της δυνητικής εξατμισοδιαπνοής μπορεί να δώσει σημαντικές επιπλέον πληροφορίες για τα χαρακτηριστικά της ξηρασίας όπως, ένταση και διάρκεια αλλά όχι και για την έναρξη της.

Λέξεις κλειδιά: SPI, SPEI, Ανάλυση Κύριων Συνιστωσών, μεταβλητότητα ξηρασίας, ανάλυση τάσεων, Σικελία.

Résumé

La surveillance de la variation des sécheresses est très importante pour la conception et la gestion des systèmes de stockage de l'eau. Au fil des années, de nombreux indice de sécheresse ont été utilisé dans cet objectif et il y a un débat actuel, dans la communauté scientifique, pour déterminer l'indice de sécheresse le plus approprié (SPI et SPEI étant les plus utilisés). Dans cette étude, une comparaison entre les deux indices sont présentés en analysant la variation de sécheresse spatiale en Sicile. Les données de précipitation et température mensuelles provenant de 50 stations météorologiques de 1921 à 2013 ont été utilisé. Pour comparer les deux indices, une analyse des composantes principales a été appliqués aux champs SPI et SPEI. Les résultats suggèrent qu'il y a une tendance générale vers des périodes plus sèches pour l'île entière et le modèle spatial caractérise uniformément la Sicile. Ce schéma de sécheresse a été enregistré par les deux indices dans les mêmes conditions. Cependant, des différences ont été observées lorsqu'une rotation varimax orthogonale a été appliquée aux composantes principales des deux indices. Bien que trois régions de conditions de sécheresse homogènes (sud, est et nord de la Sicile) aient été identifiées par les deux indices, SPI manque à la région nord pour une longue durée (36 mois), ce qui signifie que l'incorporation de la variation potentielle de la sécheresse est cruciale, au moins à l'échelle locale. Une analyse de tendance pour les composantes principales non tournées et tournées a montré que SPEI identifie des tendances plus significatives à la fois pour le cas non tourné et tourné. Enfin, l'étude de certaines sécheresses sévères survenues au cours de la période 1980-2013 a montré que la variation de la TEP peut fournir des informations supplémentaires intéressantes sur les caractéristiques des sécheresses, telles que la sévérité et la durée, mais pas sur l'apparition d'une sécheresse.

Mots-clés: SPI, SPEI, Analyse des composantes principales, Variabilité de la sécheresse, analyse de tendance, Sicile.

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1. Introduction

Droughts are extreme meteorological and hydrological hazards raising the scientific interest due to their severe impacts on the environment, societies and economies. They are considered, in a global scale, as the most costly physical disasters and because of their large spatial extent, they affect a far greater number of people comparing to other natural hazards *(Willhite, 2000)*. More than 11 million people lost their lives and more than 2 billion people, worldwide, were affected by droughts during the period 1900-2011 *(CRED, 2013)*. The number of droughts will increase on a global basis due to global warming which leads to higher temperatures and favors dry conditions *(Dai et al., 2004; Sheffield et al., 2012)*. Moreover, it is remarkable that in the last three decades there has been an increase in droughts in the European continent in terms of frequency and severity. In 2003 the most severe drought episode was recorded with its spatial extent reaching 1/3 of the European Union and affecting more than 100 million people. The economic damages of this episode were estimated to 8.7 billion euros. The Mediterranean region is affected very frequently by extreme droughts and the duration and severity of these events are constantly increasing *(Weiss et al., 2007; Vasiliades et al., 2009)*.

Due to their complex nature and their impacts on various sectors, there are many aspects in the scientific literature on the definition of droughts. This hinders the identification and monitoring of key drought characteristics, such as duration, intensity, severity, and spatial extent. Usually, they are classified into four categories according to the part of the hydrological cycle they refer to. Meteorological drought is usually caused by lack of precipitation during prolonged time periods, combined with high evapotranspiration rates. This leads to the reduction of soil moisture in the fields resulting in the second type of drought known as agricultural drought. Usually, there is a time lag to the onset of agricultural droughts in respect to that of meteorological droughts, depending on the initial moisture in the soils. Precipitation deficits will lead to a shortage in surface runoff and water stored in lakes, rivers etc., while the deficits in soil moisture will lead to a reduction in the amount of water stored in ground water reservoirs. This is the third type of droughts, the hydrological drought, which usually lasts for a certain period after the meteorological drought has ended. The last type of droughts, the socio-economic, is related to the supply-demand of different water uses such as public water supply, irrigation water uses etc. and incorporates features of all the above mentioned types types of drought *(Dracup et al., 1980; Heim, 2002)*.

Drought assessment involves the estimation of drought characteristics (severity, duration, spatial extent etc.). This is an important part in the design of hydro-technical projects as well as in water resources management and planning. The absence of a single definition for droughts has led to the development of several indicators in order to assess droughts who can be classified into meteorological, agricultural, hydrological and remote-sensing based drought indices while many scientist have done efforts to derive indices for the characterization of various types of droughts (*Keyantash & Dracup, 2002; Heim, 2002; Niemeyer, 2008; Quiring, 2009; Mishra & Singh, 2010; Zargar et al., 2011)*. These indicators are based on variables such as precipitation, temperature, potential evapotranspiration, soil moisture and other water supply related indicators. They are handy engineering tools because they incorporate the characteristics of the above mentioned drought related variables and can give valuable information in a single number which is far more useful than the raw data for decision making *(Hayes et al., 2007)*. The Palmer Drought Severity Index (PDSI; *Palmer, 1965*), the Rainfall Anomaly Index (RAI; *Van-Rooy, 1965*), the Bhalme-Mooley Drought Index (BMDI; *Bhalme & Mooley, 1980*), the Standardized Precipitation Index (SPI; *Mckee et al., 1993-1995*), the Reconnaissance Drought Index (RDI; *Tsakiris & Vangelis, 2005*), the Standardized Precipitation Evapotranspiration Index (SPEI*; Vicente-Serrano et al., 2009*) are some of the indices frequently used in a wide range of applications. For example, the PDSI index has been used in several studies in order to investigate the spatial extent and severity of drought events, to examine the spatial and temporal characteristics of droughts and, to monitor drought trends and in drought forecasting (*Karl & Quayle, 1981; Soule, 1993; Ozger et al., 2009*). The RDI index has been used in Greece for regional drought assesment in two river basins Mornos and Nestos (*Tsakiris et al., 2007*).

SPI and SPEI indexes are among the most widely used drought indices because they have some strong advantages. They are quite simple to use since a limited amount of data are required for their calculation, namely, precipitation for SPI and precipitation and potential evapotranspiration for SPEI. They can be calculated for various time scales and they can be used to make comparisons since they are standardized and the frequency of extreme drought events at any location and time scale are consistent.These two indexes were used in numerous studies in a wide range of applications. *Mishra & Singh (2009)* used the SPI index calculated for the time scales of 3 and 12 months to construct Severity-Area-Frequency (SAF) and investigate the impact of climate change in these curves on annual droughts in India. *Loukas & Vasiliades (2004)* used the SPI index in order to study the spatial and temporal characteristics of meteorological drought and provide a framework for sustainable water resources management in the region of Thessaly, Greece. *Lorenzo-Lacruz et al., (2010*) used the SPI and SPEI indexes to study the impact of climate variation on the availability of water resources in the headwaters of the Tagus River in Spain.

Recently, many researches have been conducted on the analysis of drought variability in the Mediterranean region using SPI or SPEI index. *Bordi & Sutera (2001a,b)* based on NCEP/NCAR reanalysis gridded precipitation data, performed a large scale analysis of drought variability during the last fifty years, in Europe and in Italy, using the SPI index. They showed that there is a tendency towards drier periods in the last decades for some regions. Similar results were found by Lana et al., (2001)*; Tsakiris & Vangelis, (2004)*. Moreover, *Bonaccorso et al., (2003)* used SPI index to perform drought analysis based on NCEP/NCAR reanalysis precipitation data, as well as, precipitation data observed in 43 gauges. They applied Principal Components Analysis (PCA) to study the long term drought variability in Sicily. They found that there is a significant trend towards drier periods during the last decades starting from the seventies onward and this trend characterizes uniformly the entire Island. Moreover, they highlighted three regions within the Island with homogeneous drought conditions after an orthogonal rotation was applied to the principal component patterns.

The above study is a comprehensive approach to the analysis of spatial variability of droughts. Even though precipitation based drought indices like SPI have been successfully used in numerous applications, many researchers raise awareness for neglecting the effect of temperature on drought conditions especially when there is evidence for temperature rises. It has been demonstrated that there is a temperature increase *(Jones & Moberg, 2003; Sheffield et al., 2012)* which leads to more severe drought events and therefore the role of temperature in drought assessment is crucial *(Rebetez, et al., 2006; Mavromatis, 2007)*.

In this study an analysis of long term drought variability in Sicily is performed. Drought occurrence is estimated using SPI and SPEI indexes, based on precipitation and temperature data observed in 50 gauges located uniformly over Sicily Island. Principal component analysis is applied in order to describe the major spatial patterns of drought and examine the differences between the two indices. The purpose of this research is to examine if the incorporation of the temperature variability and consequently of potential evapotranspiration variability will yield additional valuable information in drought analysis comparing to the results of SPI. Moreover, a trend analysis is conducted in order to investigate the significance of the trends identified by the two indexes allowing for further comparisons between the two indexes. Finally, a more detailed investigation of some selected severe drought events is done in order to compare the behaviour of the two indexes in specific events in terms of their ability to capture the onset of droughts and quantify the duration and severity of the events.

The rest of this article is structured in four sections.In section 2 the study area and the data that were used are described. In the following section the methodology that was followed is presented. In the third section the results are presented and discussed. In the final section the conclusions of this article are presented.

2. Study Area – Data

2.1 Study Area

The study area of this project is Sicily Island located in southern Italy. Sicily has a Mediterranean climate and belongs to the CSa climatic division of Koppen Geiger climate classification system according to *Peel et al., (2007)*. This means that Sicily has mild and wet winters and hot and dry summers. Precipitation is highly variable especially during winter. A map of Sicily is given in Figure 1.

Figure 1 Map of Sicily along with the meteorological stations.

Sicily is the biggest island in Italy and in the Mediterranean region. Its terrain is mostly hilly and it is intensively cultivated wherever possible. It is drained by several rivers mostly in the central part of the island. Located in the mediterranean region the last decades Sicily has experienced some severe drought events. One of the most severe droughts occurred the summer of 2003 causing severe damages to local economy and agriculture. In this study, long term drought variability will be studied for the whole area of Sicily except for some small islands loacated around it.

2.2 Data

Monthly precipitation (given in mm) and temperature (given in ^{o}C) data observed in 50 meteorological stations over Sicily Island were used to compute the SPI and SPEI indexes. The data cover a historical period from January 1921 until December 2013. The data were provided by the Laboratory of Hydraulics of the Department of Civil and Environmental Engineering of the University of Catania.

The selection of the meteorological stations from which the precipitation and temperature data were extracted, was done based on two criteria. Firstly, the length of the time series had to be long enough in order for the parameters of the index and the significance of the drought trends to be estimated in a reliable and objective way. Moreover, the stations should be distributed homogeneously over the Island. The quality of the data has been checked and they were successfully used in previous studies *(Bonaccorso et al., 2003)*. The locations of the stations are shown in Figure 1.

Table 1 Characteristics of the meteorological stations

ID	Station_Name	Elevation	Latitude	Longitude
70	CASTROREALE	383	38.1	15.212
130	MONTALBANO ELICONA	929	38.024	15.018
220	TORTORICI	482	38.032	14.825
310	SAN FRATELLO	690	38.017	14.602
320	CARONIA	302	38.034	14.436
360	TUSA	497	37.975	14.237
430	CASTELBUONO	380	37.931	14.09
470	CEFALU`	30	38.036	14.017
660	CIMINNA	525	37.894	13.56
780	VILLA PIOPPO	380	38.051	13.236
875	PALERMO (OSSERVATORIO)	37	38.111	13.351
950	SAN GIUSEPPE JATO	462	37.975	13.188
1050	SAN VITO LO CAPO	3	38.189	12.733
1030	TRAPANI	2	38.015	12.507
1060	FASTAIA	182	37.931	12.742
1110	CIAVOLO (CONTRADA)	128	37.762	12.551
1120	MARSALA	12	37.812	12.457
1180	PARTANNA	407	37.731	12.892
1270	CORLEONE	588	37.816	13.302

1300	ROCCAMENA	480	37.836	13.154
1360	SAMBUCA DI SICILIA	296	37.651	13.119
1400	SCIACCA	118	37.514	13.127
1430	PALAZZO ADRIANO	679	37.688	13.379
1480	BIVONA	521	37.621	13.44
1560	SAN CATALDO	643	37.484	13.986
1600	SANTA CATERINA VILLERMOSA	606	37.59	14.03
1700	RACALMUTO	450	37.411	13.73
1760	CATTOLICA ERACLEA	150	37.442	13.397
1810	AGRIGENTO (ISPETTORATO)	175	37.305	13.589
1860	PETRALIA SOTTANA	932	37.82	14.094
1900	ALIMENA	775	37.707	14.122
2020	CALTANISSETTA	597	37.498	14.058
2100	SOMMATINO	349	37.339	13.996
2200	LICATA	70	37.1	13.933
2220	BUTERA	390	37.19	14.185
2240	GELA	30	37.065	14.252
2250	PIAZZA ARMERINA	640	37.39	14.37
2370	RAGUSA	515	36.924	14.724
2380	MODICA	370	36.861	14.763
2470	PALAZZOLO ACREIDE	695	37.063	14.9
2580	LENTINI CITTA'	43	37.293	14.999
2690	CESARO'	1100	37.787	14.833
2790	BRONTE	780	37.834	14.719
3050	CALTAGIRONE	608	37.241	14.519
3110	ZAFFERANA ETNEA	590	37.696	15.106
3120	LINGUAGLOSSA	530	37.841	15.145
3150	ACIREALE	194	37.622	15.166
3155	CATANIA (Ist. Agrario)	75	37.519	15.072
3210	FLORESTA	1270	37.988	14.909
3400	GANZIRRI	3	38.258	15.609

3. Methodology

3.1 SPI and SPEI indexes

Droughts are insidious natural hazards and maybe the least understood of all the weather phenomena. One of the main differences with other hazards is that they are slowly developing phenomena and they propagate through the whole hydrological cycle. Therefore, monitoring droughts is a crucial part of drought analysis and it is the first step in the methodology followed for the purposes of this project.

Among the numerous drought indicators proposed over the years (*Mishra & Singh, 2010; Zargar et al., 2011*) SPI and SPEI indexes are among the most commonly used and they were chosen for the analysis of this project. The reason behind this choice is their strong advantages over other indexes. Firstly, they can be computed for a wide range of time scales. It is worth to recall that drought is a mulitscalar phenomenon and the water deficits accumulated in a given usable water resource varies in respect with time. Therefore, computing SPI and SPEI in different time scales will allow to monitor different drought types and drough conditions in hydrological subsystems. Normally, shorter time scales (1-6 months) are related to soil water content and river discharge, medium time scales (6-12) to discharge in medium course of the rivers and long time scales (12, 24 and 36) to ground water variation.Moreover, they are simple to compute since only precipitation data (for SPI) and precipitation and potential evapotranspiration data (for SPEI) are required. They allow to make comparisons since they are standardized indices and the frequency of extreme drought events at any location and time scale are consistent.

In this project SPI and SPEI indexes were calculated for the time scales of 1, 3, 6, 12, 24 and 36 months in 50 meterological stations distributed uniformly over Sicily. The computation of SPI involves the fitting of the Gamma distribution to the precipitation data for each month and the parameter estimation for the corresponding months for the time scales under consideration. It is worth to mention that different distribution functions could have been used. However, *Bonaccorso et al. (2003)* tested the fitting of several distribution functions in 43 gauges in the island and they found that Gamma distribution was the most appropriate one. Moreover, recently *Stagge et al., (2015)* proposed the gamma distibution as suitable distribution for the calcualtion of SPI and the GEV or the log-logistic distributions for the calculation of SPEI, in Europe.

In this study, the fitting of the distribution was done using the Unbiased Probability Weighted Moments method *(Hosking, 1986)*. The gamma function is given in the following equation (1):

$$g_{(x)} = \begin{cases} \frac{1}{\beta^{\alpha}\Gamma_{(\alpha)}} x^{\alpha-1} e^{\frac{-x}{\beta}}, & \chi > 0 \\ 0, & elsewhere \end{cases} \quad (1)$$

Where α, β, x > 0, are the shape and scale parameters and precipitation amount respectively. The $\Gamma_{(\alpha)}$ is the gamma function given in equation (2):

$$\Gamma_{(\alpha)} = \int_0^{\infty} y^{\alpha-1} e^{-y}\, dy \quad (2)$$

The estimated parameters are then used to calculate the cumulative probability distribution (equation 3) for a specific precipitation event, which has been observed on a defined time scale (month). Gamma function is not defined for zero values. However there is large number of zero rainfall occurrences as moving to shorter time scales; cumulative distribution is therefore modified (equation 5) to include these events *(Panofsky & Brier, 1958)*.

$$G_{(x)} = \frac{1}{\beta^{\alpha}\Gamma_{(\alpha)}} \int_0^{x} x^{\alpha-1} e^{\frac{-x}{\beta}}\, dx \quad (3)$$

Substituting t for –x/β yields the incomplete gamma function given in equation (4):

$$G_{(x)} = \frac{1}{\Gamma_{(\alpha)}} \int_0^x x^{a-1} e^{-t}\ dt \quad (4)$$

$$H_{(x)} = q - (1 - q) G_{(x)} \quad (5)$$

Where q is the probability of zero rainfall occurrences for a specific time scale.

The new cumulative probability distribution is then transformed into a standardized normal distribution Z (equation 6) with the average equal to 0 and the standard deviation equal to 1 *(Abramowitz & Stegun, 1964)*. SPI is the number of standard deviations left (drought) or right (wet) from 0. In this way, SPI has fixed expected value and standard deviation, which is a precondition for comparing index values between different locations or regions.

$$SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad for \quad 0.5 < H_x < 1 \quad t = \sqrt{ln\left(\frac{1}{(H_x)^2}\right)}$$
$$SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad for \quad 0 < H_x < 0.5 \quad t = \sqrt{ln\left(\frac{1}{(1 - H_x)^2}\right)} \quad (6)$$

Where c_0=2.515517, c_1=0.802853, c_2=0.010328, d_1=1.432788, d_2=0.189269, d_3=0.001308. Drought events can then be classified into categories such as moderate drought, extreme drought etc. according to *Mckee et al. (1993)* criteria. In Table 2 the classification system for drought events is shown.

Table 2 Classification system of droughts using SPI and SPEI indexes

SPI Value	Category	Probability (%)
2.00 or more	Extremely wet	2.3
1.5 to 1.99	Severely wet	4.4
1 to 1.49	Moderately wet	9.2
0 to 0.99	Mildly wet	34.1
0 to -0.99	Mild drought	34.1
-1 to -1.49	Moderate drought	9.2
-1.5 to -1.99	Severely drought	4.4
-2 or less	Extremely drought	2.3

The methodology for the computation of SPEI index is the same. The only differences are that SPEI uses a climatic water balance as data, which is defined as the difference between the Precipitation and PET. Moreover, the log-logistic distribution is fitted to the data and not the gamma distribution. The reason is that gamma is a two parameter distribution with a range of values 0>x<∞ therefore it cannot take negative values. On the other hand the log-logistic is a three parameter distribution and can take values in the range γ>x<∞, where γ is the parameter of origin of the distribution, thus SPEI can take negative values. The log-logistic distribution is given in equation (7):

$$f_{(x)} = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left[1 + \left(\frac{\chi-\gamma}{\alpha}\right)^{\beta}\right]^{-2} \quad (7)$$

Where α, β, γ are the scale, shape and origin parameters respectively. More details about the SPEI computation can be found in *(Vicente-Serrano et al., 2009)*.

The PET was calculated using Thornthwaite equation *(Thornthwaite, 1948)*. The reason is because it is simple and only temperature data are required. However, even if more data were available and it was possible to estimate PET using a more sophisticated method such as Penman Monteith the differences in the SPEI series would be trivial. This is likely to happen because the two main variables (Precipitation and PET) are standardized as one (Climatic water balance) and not separately. In this way the additional information included in the PET series would be lost in the standardization process. This is also reported by *Vicente-Serrano et al., (2009)* and *Mavromatis, (2007)*.

3.2 Correlation Analysis

A correlation analysis was conducted for the two indices in order to find in which time scale they are better correlated. The r-Pearson correlation coefficient was used to compute the correlation and the analysis was performed for all the time scales. In order to achieve a better visualization of the results, the values of correlations were interpolated to produce maps of Sicily with the correlations for all the time scales. Ordinary kriging was used as an interpolation method. Ordinary kriging is based on a semi-variogram model (equation 8) which measures the dissimilarity between observations.

$$\gamma_h = \frac{1}{2n}\sum_{i=1}^{n}\{Z(x_i) - Z(x_i + h)\}^2 \quad (8)$$

Where n is the number of pair of data points separated by a distance h, $Z(x_i)$ and $Z(x_i+h)$ are the values of variable Z at x_i and x_i+h locations.

The predicted values at the unsampled locations are given by equation (9):

$$Z(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \quad (9)$$

A theoretical variogram model is fitted to the experimental variogram of the data. The fitting is performed using the weighted least square technique *(Cressie, 1985)*. Among the theoretical models (available in the ArcGis environment) the two parameter gaussian model was used to fit the experimental variogram.

The weights (λ_i) of equation (9) are obtained by minimizing the variance between observations and estimations and ensuring that the estimator will be unbiased. In the case of ordinary kriging the estimator is the mean but it is assumed to be constant. The method of Langrange multiplier is used to estimate the weights.

Ordinary Kriging was chosen as the interpolation method because it provides estimation of the errors of the model used. The cross validation technique *(Dubrule, 1983)* was used to derive diagnostic statistics such as mean error, root-mean-square-error, mean standardized error, root-mean-square-standardized-error and average standard error. These statistical indices were used to evaluate the ability of the model to make predictions. More details about kriging and ordinary kriging can be found in *(Goovaerts, 1997)*.

3.3 Principal Components Analysis (PCA)

Studying long-term drought variability in Sicily based on the results of SPI and SPEI indexes for 6 time scales on 50 meteorological stations is a quite complex task. Therefore, PCA has been applied to the SPI and SPEI fields for all the time scales. PCA is a standard statistical method which is used frequently in meteorological studies in order to reduce the dimensionality of the problem and make the variables under study easier to interpret. This is achieved by constructing new linearly uncorrelated (orthogonal) variables from the original correlated ones based on the variance-covariance structure of the original variables. The new variables are linear combinations of the original ones. The coefficients of the linear combinations are called "Loadings" and they represent the weight of the original variables. Moreover, there is a condition in PCA that makes it very useful. The first of the new variables is constructed in such a way in order to explain as much of the original variance as possible. The second one retains as much of the remaining variance as possible, and so on and so forth. In the end, it is possible to work only with the first few variables which account for most of the total variance achieving in this way some economy. However, the number of the important components to keep is a tricky process and many methods have been proposed over the years for this purpose *(Zwick & Velicer, 1986, Velicer et al., 2000)*. One of the most, reliable methods is the Velicer's Minimum Average Partial criterion (MAP) *(Velicer, 1976a,b)* and it is the one used in this project to extract the appropriate number of principal components.

Briefly, the PCA involves the computation of eigenvalues and eigenvectors of the covariance matrix. The eigenvectors (loadings) are previously properly normalized and in this study represent the spatial patterns and thus the correlation between the new principal components time series (scores) and observation time series. The eigenvalues are the fraction of the total variance explained by each loading.

Another, useful aspect of PCA is the rotation of the principal components (eigenvectors) which leads to higher correlation of the loadings with a smaller set of spatial variables and lower correlation with the remaining variables. Varimax rotation is one of the most commonly used methods to rotate the principal components. It involves an orthogonal rotation of the principal components in a way that maximizes the variance of the squared loadings of principal components on all the variables. In this study a varimax rotation was applied to the principal components allowing the identification of regions within the island that have homogeneous drought conditions.

More details about the PCA and the varimax rotation can be found in *(Kottegoda & Rosso, 2008)*. It must be mentioned that the loadings of the unrotated and rotated principal components were interpolated using ordinary kriging to derive maps of Sicily in order to achieve a good visualization of the drought variability spatial patterns existing in the island for the period 1921-2013.

3.4 Trend Analysis

Trend analysis was performed in order to investigate and test, the existence and significance of possible trends. This will allow further comparisons between the two indexes. The analysis was performed for both indexes and for all time scales. The first unrotated principal components time series as well as the time series of the rotated principal components corresponding to the regions of homogeneous drought conditions identified in this study were used to investigate the existence of possible trends. The significance of the trends was tested using the modified Trend Free Pre-Whitening Mann Kendall's (TFPW-MK) test as described by *Yue et al., (2002)*. The choice of this test is motivated by the fact that the SPI and SPEI series are highly autocorrelated for long time scales. The existence of serial correlation could increase the probability of detecting a trend using the standard Mann Kendall trend test and falsely reject the null hypotheses of no trend *(von-Storch, 1995)*. The pre-whitening procedure, which removes the serial autocorrelation, was first proposed by *von-Storch, (1995)* and it has been used in several studies *(Douglas et al., 2000; Zhang et al., 2001)*. *Yue et al., (2002)* reported that an existing trend may have also an impact in the serial correlation of a time series. Therefore, they proposed the TFPW-MK in order to prevent the impacts of both serial autocorrelation in trend and vice versa.

The standard Mann Kendall test is a non-parametric test for trends in which the n time series values (X_1, X_2, X_3, ….., X_n) are replaced by their relative ranks (R_1, R_2, R_3, ….., R_n) starting at 1 for the lowest up to n. The test statistic can be calculated using the equation (10):

$$S = \sum_{i=1}^{n-1}\left[\sum_{j=i+1}^{n} sgn\left(R_i - R_j\right)\right] \quad (10)$$

Where sgn(x)=1 for x>0, sgn(x)=0 for x=0 and sgn(x)= -1 for x<0. If the null hypotheses (H_0) of no trend is true then S is approximately normally distributed with μ=0 and σ=n(n-1)(2n+5)/18. The z-statistic and the probability value P of the statistic S can be obtained by equations (11) and (12):

$$Z = \frac{|S|}{\sigma^{0.5}} \quad (11)$$

$$P = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{\frac{-t^2}{2}} dt \quad (12)$$

The critical test statistic values for various significance levels can be obtained from normal probability levels.

The TFPW-MK test follows some steps before applying the Mann Kendall test on the time series. Firstly, the slope of the time series data is estimated using the Thiel Sen's approach *(Theil, 1950a-c; Sen, 1968)* and the trend is assumed to be linear only if the slope differs from zero. Otherwise, there is no need to continune the process. After the trend has been estimated the data are detrended. The serial autocorrelation of lag-1 is then removed from the detrended series and the new time series is called the trend free pre-whitened series (TFPW). The process continues by blending together the trend and the TFPW series and finally the Mann Kendall's test is applied on the blended series.

More details about the TFPW-MK and Mann Kendall's test can be found in *Yue et al., (2002)* and references therein.

3.5 The run sum analysis method

As mentioned in the introduction the behavior of the two indices to monitor some selected severe drought events was investigated. In order to do that it was necessary to extract the characteristics of the drought events. Many methods have been proposed over the years for this purpose. The most commonly used one is the run sum analysis method proposed by *Yevjevich, (1967)*. In this method a threshold water demand level is predefined (here -1) and drought or wet periods can be determined as a sequence of consecutive intervals where the variable remains below or exceeds this threshold. In this way a drought event can be characterized by three properties: the drought duration the severity or volume of deficits and the drought intensity. As drought duration is considered the time period during which the variable remains under the threshold while severity is defined as the sum of single deficits for the corresponding drought duration. Drought intensity is the ratio of the accumulated deficit (severity) to the drought duration. The onset of a drought event is when the variable falls below the threshold for the first time. A graphical representation of the method is given in Figure 2.

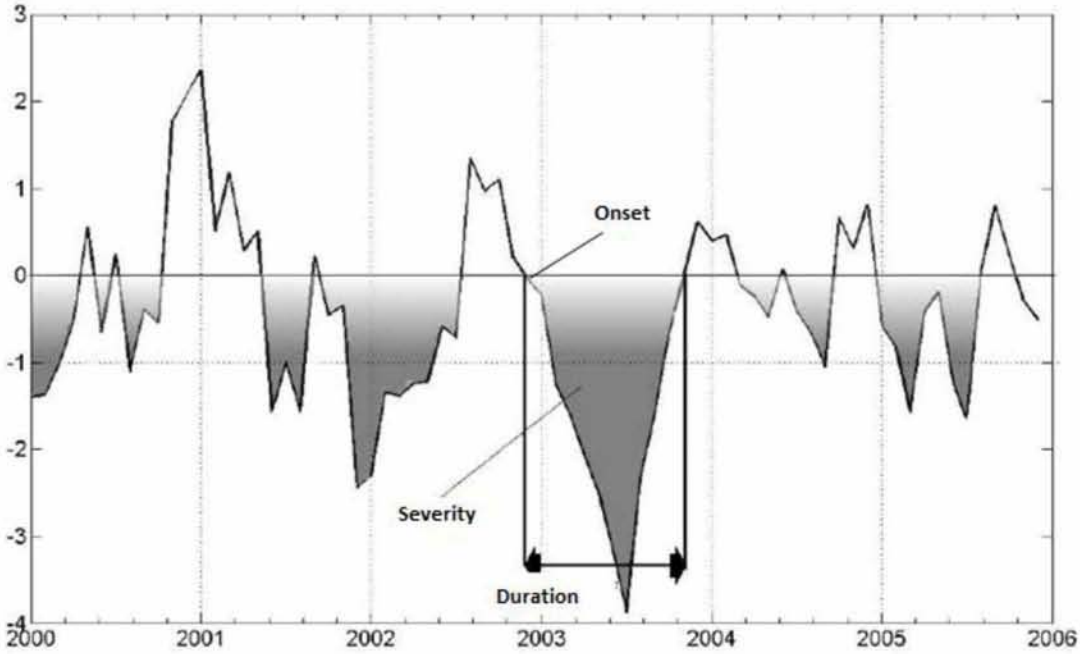

Figure 2 Characteristics of drought events.

4. Results and Discussion

4.1 SPI and SPEI indexes

The SPI and SPEI indexes were calculated at the 50 stations considered in this project, for the time scales of 1, 3, 6, 12, 24 and 36 months. It should be mentioned that the indexes have both similarities and differences for the different stations as well as for the different time scales. However, it is not wise to examine the results for each of the stations and time scales separately. For this reason the main comparisons will be done for the correlation analysis, PCA, trend analysis and for the characteristics of the severe drought events as derived by the two indexes.

4.2 Correlation Analysis

To begin with the correlation analysis, maps of Sicily representing the correlation existing between the two indices for all the time scales are shown in Figure 3. The results suggest that there is strong correlation between the two indexes for all the time scales ($r \geq 0.78$). The strongest one is observed for the time scale of 12 months where the highest values of correlation ($r \geq 0.89$) are covering the whole island. Moreover, it is observed that as the time scale increases the correlation between the two indexes becomes stronger. This is reasonable since the PET variability becomes lower for longer time scales while for the precipitation this is not true.

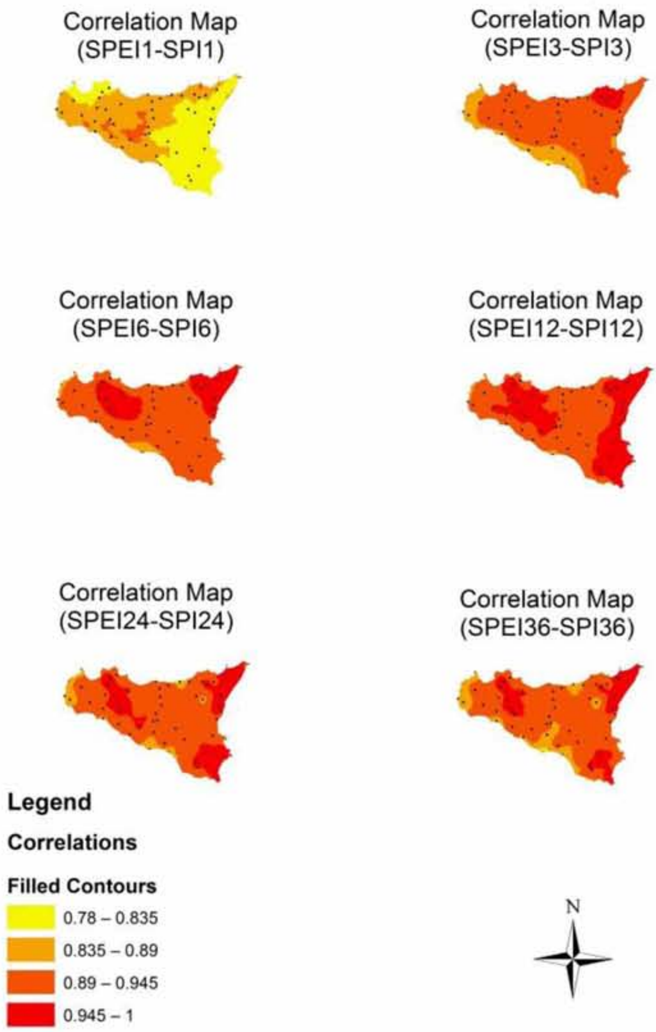

Figure 3 Map of Sicily showing the correlation between the SPI and SPEI for various time scales.

However, it must be noted that the correlations for the time scale of 36 months are slightly lower than those of 12 or 24 months. Among the 50 stations used in this study some of them show significant increasing trends is temperature. According to *Vicente-Serrano et al., (2009)* the correlation between the two indexes may decrease in longer time scales when there are apparent trends in temperature.

4.3 Principal Component Analysis

Principal Components Analysis has been applied to SPI and SPEI fields for all the time scales. Maps of Sicily representing the loadings (spatial patterns) of the first 8 unrotated principal components of SPI and SPEI for the time scale of 12 months are shown in Figure 4. The variance explained by each of the principal components is shown in Table 3. Even though the number of important components to keep according to MAP criterion was 10, here only the first 8 are presented because the major patterns of drought variability emerge in the first few components.

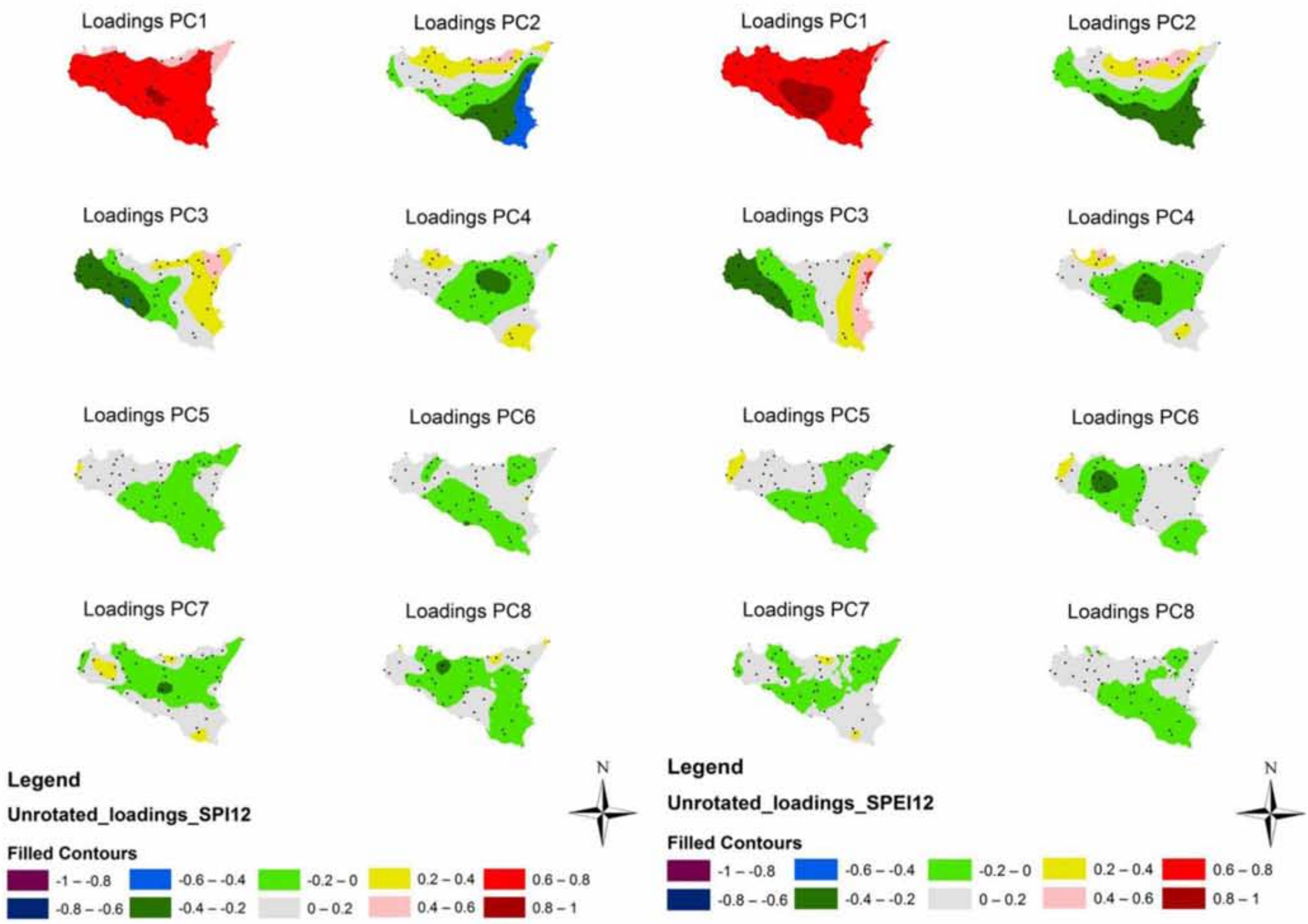

Figure 4 Maps of Sicily representing the loadings of the first 8 unrotated principal components for SPI and SPEI indexes for the time scale of 12 months.

Table 3 Proportion of Variance explained by each of the first 8 principal components for the unrotated and rotated case for the time scale of 12 months.

	SPI index				SPEI index	
Unrotated Principal Components	Variance (%)	Rotated Principal Components	Varimax (%)	Variance (%)	Rotated Principal Components	Varimax (%)
PC1	46.7	RC1	21.2	53.29	RC1	24.1
PC2	7.9	RC2	15.9	7.24	RC2	17.6
PC3	6.7	RC7	8.8	7.01	RC3	14.8
PC4	3.4	RC4	7.6	3.67	RC5	6.9
PC5	3.1	RC5	6.9	3.37	RC4	6.4
PC6	2.7	RC8	5.9	2.22	RC10	3.8
PC7	2.4	RC3	4.1	1.91	RC6	3
PC8	2	RC9	2.9	1.85	RC7	2.1

The results suggest that the first principal components show the highest values of loadings, for the entire island for both indexes and the main spatial patterns of these two components characterize Sicily uniformly. Moreover, the proportion of variance explained by the first principal components (Table 3) is the highest. This means that the long-term drought variability in Sicily is mainly represented by the scores of the first principal components. Furthermore, the values of the loadings for the less significant components are quite lower, there are no specific spatial patterns and the proportion of variance explained is quite lower when compared to the first ones. Comparing the results for the two indexes, it can be seen that they are very similar. The spatial patterns of the first principal components are almost the same, but in case of SPEI, the loadings are higher and correspond to a wider extent than SPI. This is observed for example in the central part or in some regions in the northern and north-eastern part of Sicily. The patterns of the two indexes for the rest principal components are quite similar. In Figure 5 there are plots with the scores (time series with the values of the indexes) of each of the unrotated principal components for both indexes for the time scale of 12 months. The results suggest that there is a multiyear variability and a common tendency towards drier periods starting from the 80s onward and then a slight increasing tendency starting from the 00s onward. This is evident in the scores of the first principal components. The scores of the rest components do not show any specific pattern.

The orthogonal varimax rotation revealed useful information about the way the general drought pattern covering the whole island appears in a local scale within the island. Figure 6 shows the loadings of the first 8 rotated principal components for the two indexes for the time scale of 12 months. The rotated components are ordered in respect with the proportion of relative variance they account for (Table 3). It must be noted that the first three rotated components which explain most of the variation characterize three regions within the Island that mostly correlate to the corresponding scores: eastern, southern and northern Sicily. Even though, the results of the two indexes are quite similar they show some interesting differences. The three areas of homogeneous drought conditions are generally wider in the SPEI case than in the SPI, especially for the northern region. This is a first indication that PET variability may play an important role in monitoring drought variability in a more local scale. Moreover, the relative variance explained by the first three rotated components is generally higher in the case of SPEI. This means that the three regions can be identified by both indexes but the sensitivity to drought variability is different. The scores of the corresponding rotated principal components are shown in Figure 7. The scores of the first (southern region) rotated principal components reveal a decreasing tendency towards drier periods starting from the 80s onward for both indexes. On the other hand the rotated components corresponding to the eastern and northern regions show increasing trends starting from the 80s onward for both indexes. The significance of these trends is discussed later in this section.

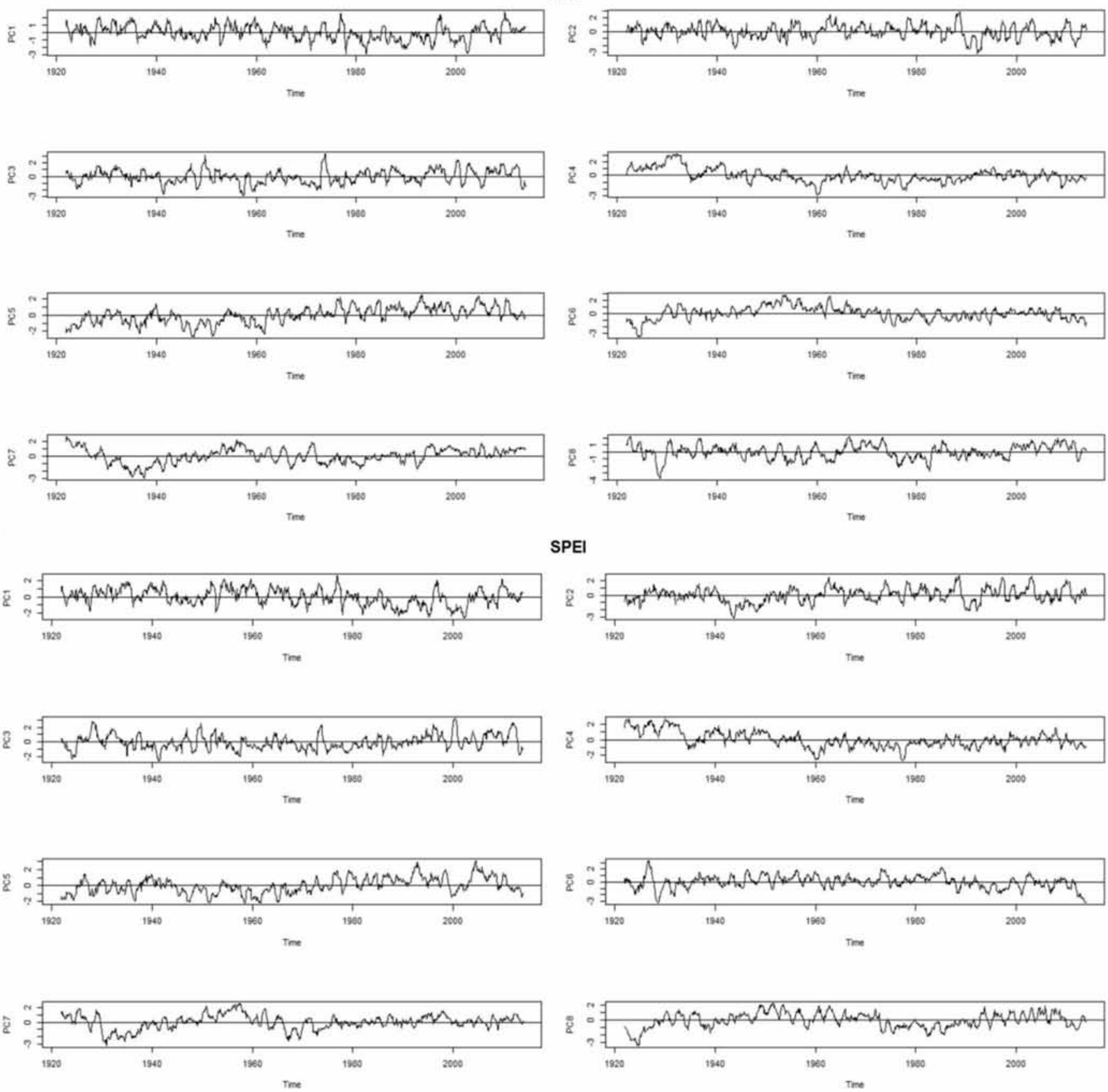

Figure 5 Scores of the first 8 unrotated principal components for SPEI and SPI indexes for the time scale of 12 months.

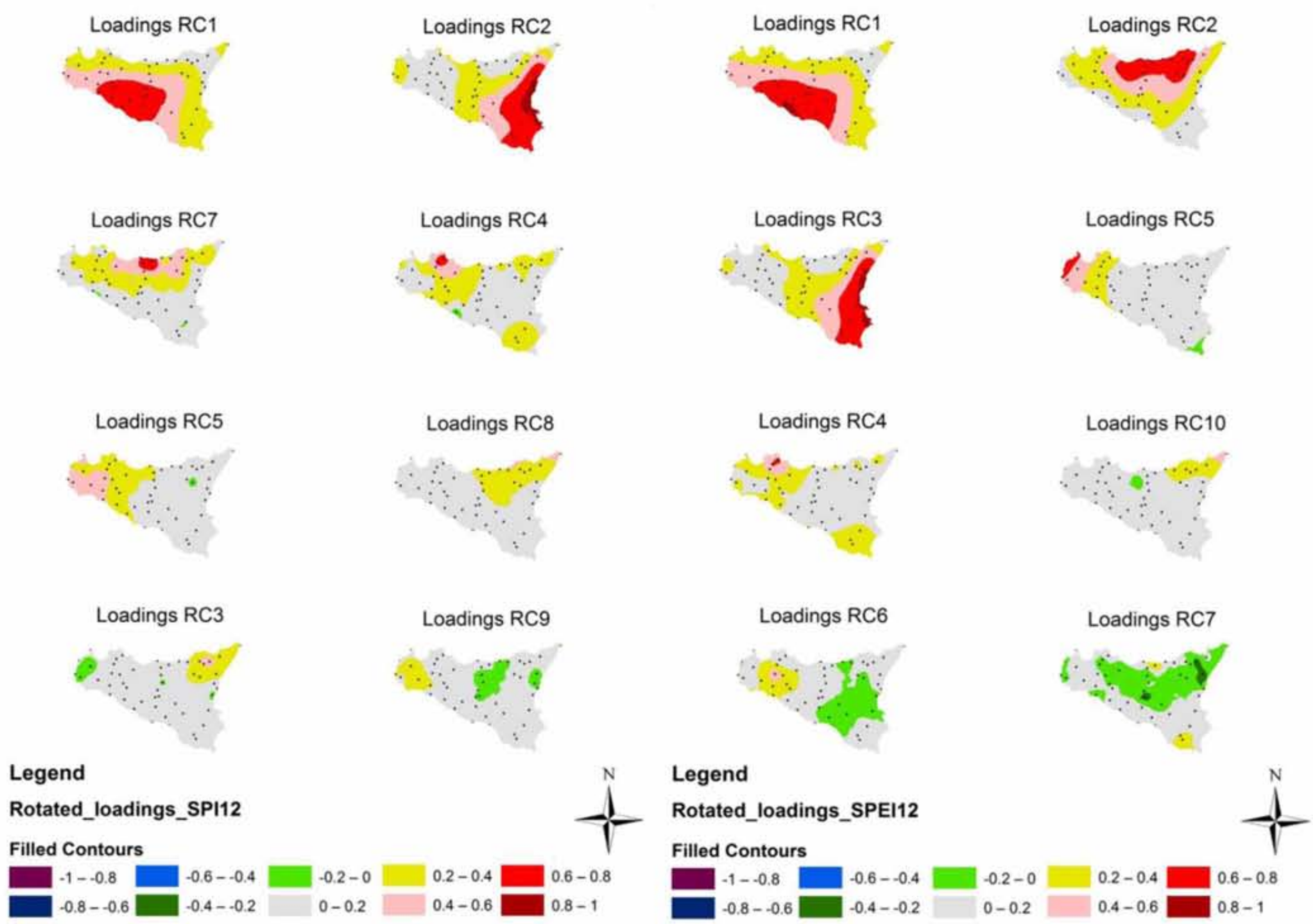

Figure 6 Maps of Sicily representing the loadings of the first 8 rotated principal components for SPI and SPEI indexes for the time scale of 12 months.

Concerning the results for the time scale of 24 months it can be observed that they follow the same pattern. The first principal components still explain most of the variation (Table 4) and the spatial patterns of their loadings (Figure 8) characterize Sicily Island uniformly. Examining the scores for the unrotated case (Figure 9) the general tendency towards drier periods can be identified in this case too but it lasts until the 90s. When the rotation was applied the same three regions of homogeneous drought conditions (Figure 10) were identified but examining the relative variance of the rotated components, shown in Table 4, there are differences in the case of SPI 12 (This is also true when comparing the relative variance explained by the components of the two indexes). This means that the main spatial pattern of drought conditions existing in the island can still be subdivided in the same three regions but the sensitivity to drought variability is different in each time scale and thus different mitigation measures should be examined for each time scale. Concerning the scores of the rotated components (Figure 11) corresponding to the three regions with homogeneous drought conditions it can be observed that for the southern region there is again a decreasing trend while for the southern and eastern ones increasing trends.

The results for the SPI index for the time scales of 12 and 24 months are quite similar with those reported by *Bonaccorso et al., (2003)*. We only mention SPI because in that study only SPI index was used to monitor the drought conditions in Sicily.

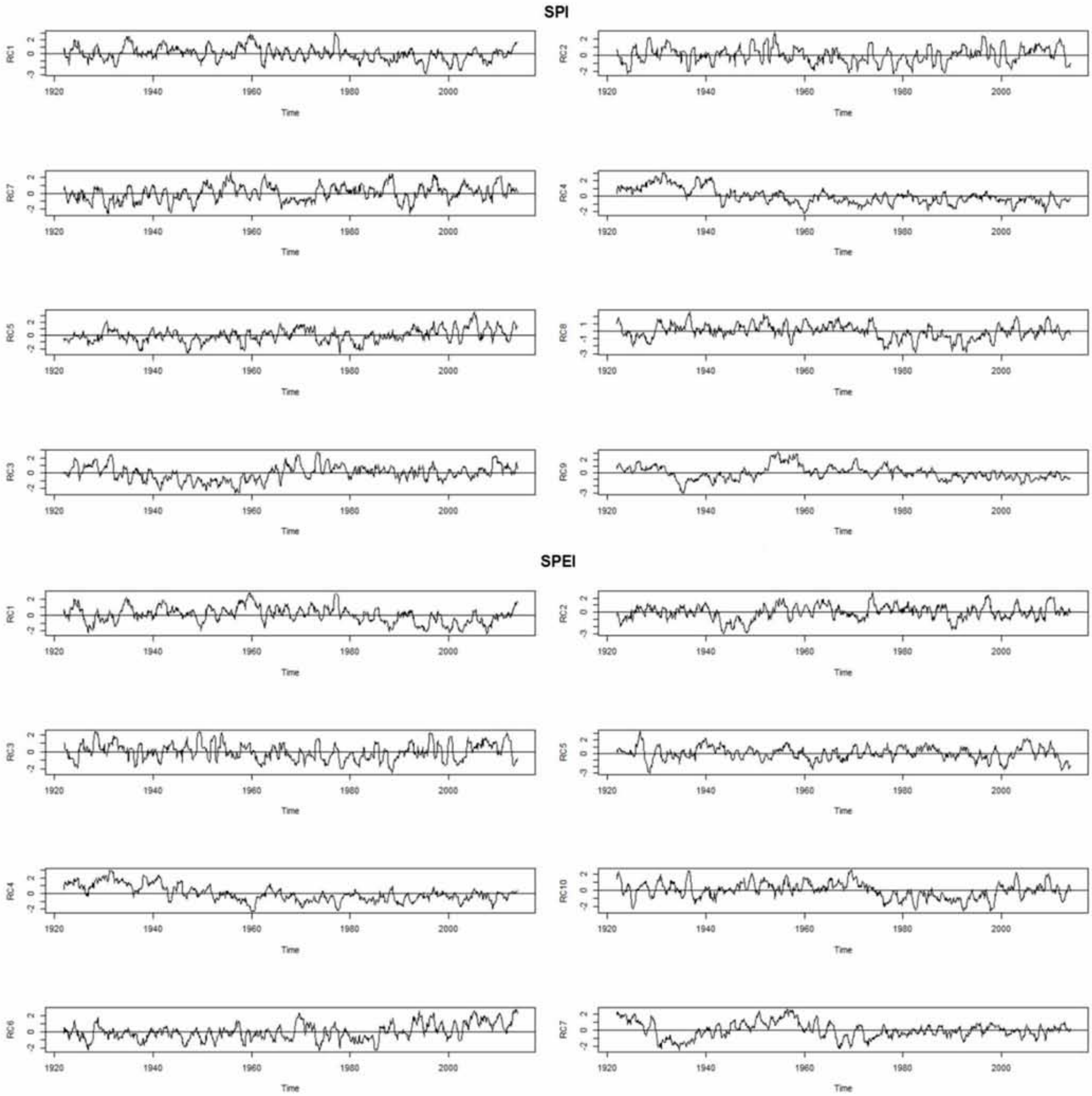

Figure 7 Scores of the first 8 rotated principal components for SPEI and SPI indexes for the time scale of 12 months.

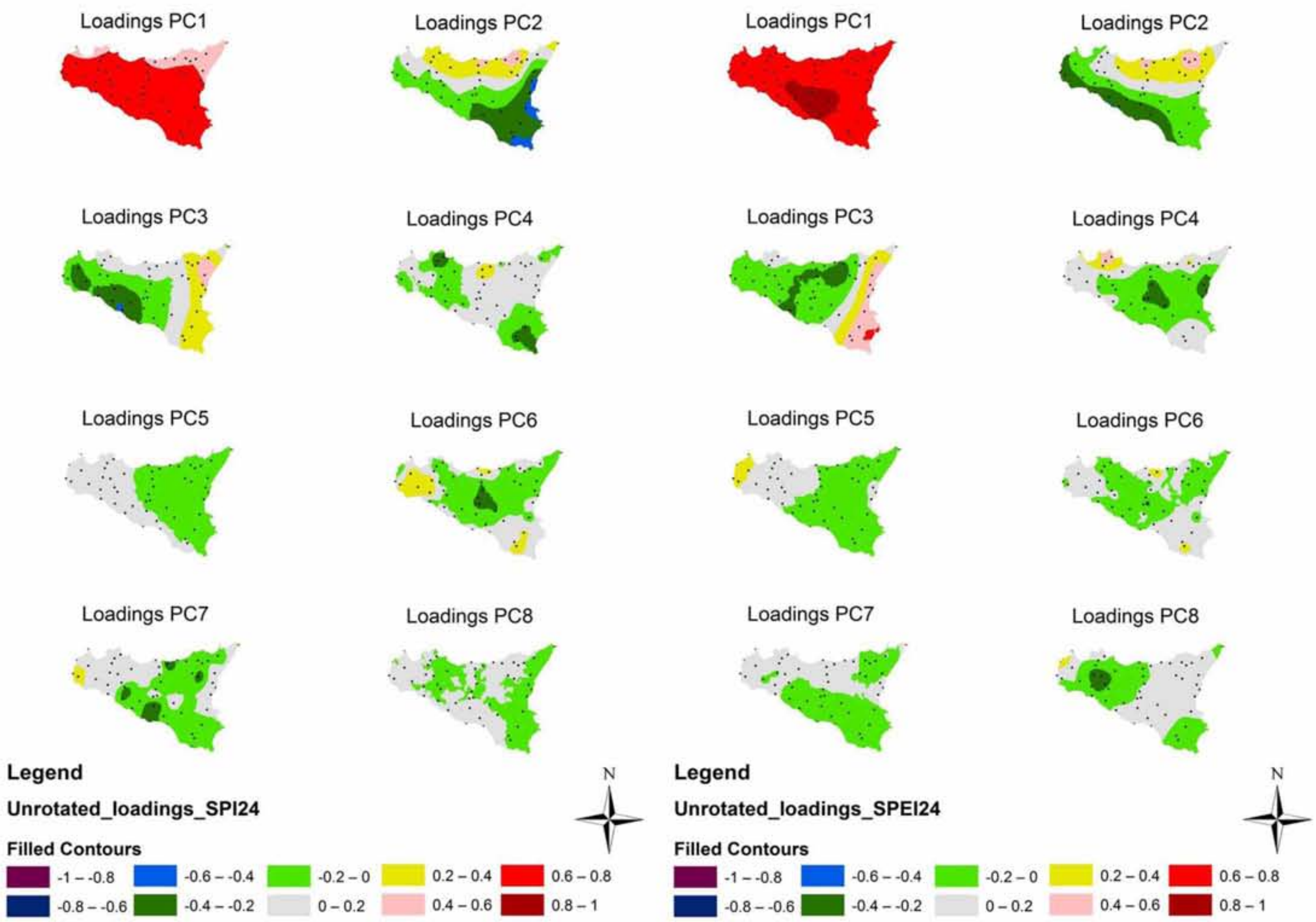

Figure 8 Maps of Sicily representing the loadings of the first 8 unrotated principal components for SPI and SPEI indexes for the time scale of 24 months.

Table 4 Proportion of Variance explained by each of the first 8 principal components for the unrotated and rotated case for the time scale of 24 months.

	SPI index				SPEI index	
Unrotated Principal Components	Variance (%)	Rotated Principal Components	Varimax (%)	Variance (%)	Rotated Principal Components	Varimax (%)
PC1	45	RC1	17.4	52.6	RC1	25.6
PC2	7.4	RC3	13.4	7.7	RC2	18.2
PC3	6.6	RC2	9	6.8	RC3	12.9
PC4	4.5	RC9	8.5	4.1	RC4	8.8
PC5	4	RC4	7.5	3.7	RC5	4.6
PC6	3.2	RC6	6.3	2.4	RC9	4.2
PC7	3	RC7	5.8	2	RC7	2.9
PC8	2.4	RC5	5.1	2	RC6	2.7

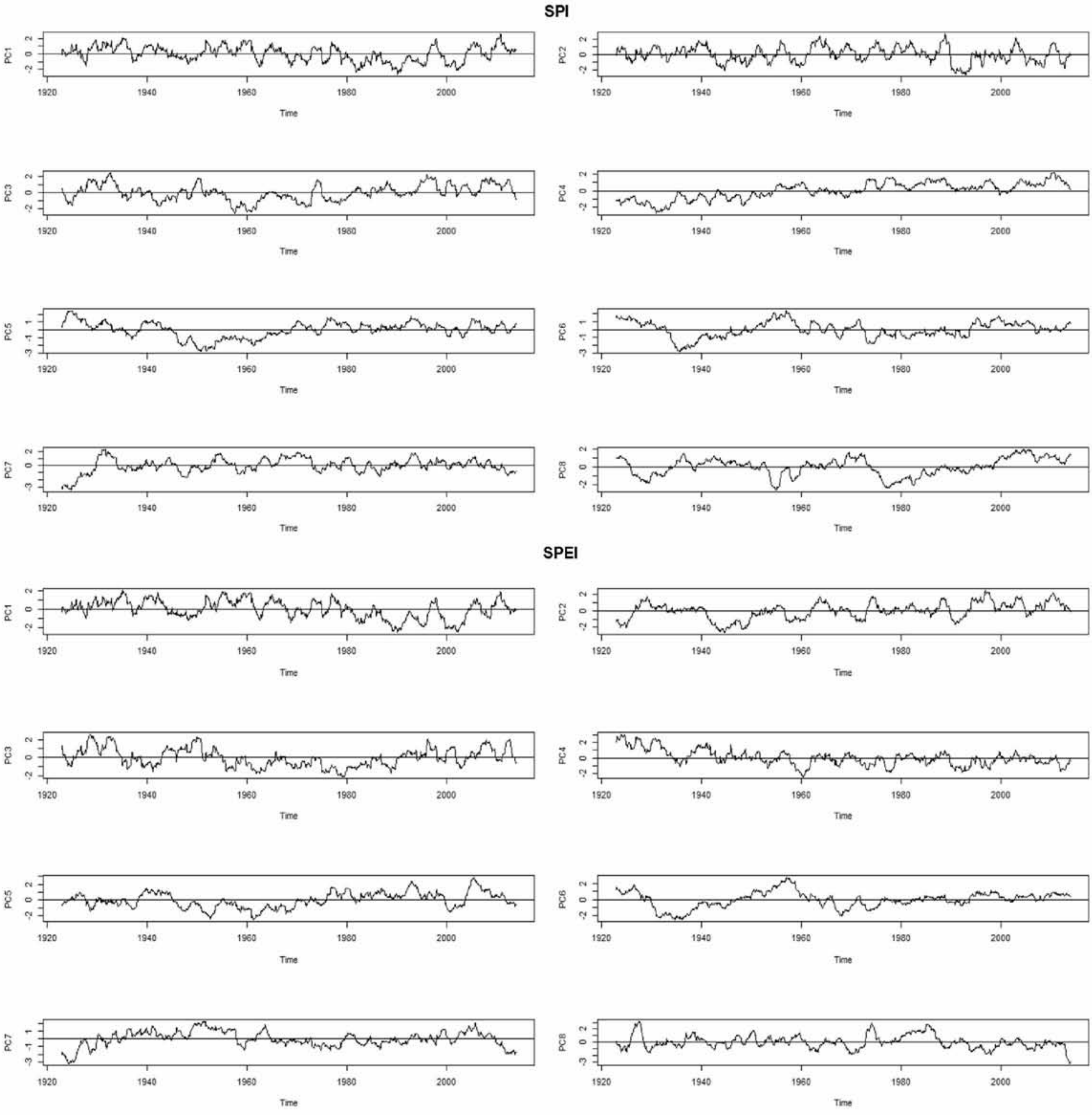

Figure 9 Scores of the first 8 unrotated principal components for SPEI and SPI indexes for the time scale of 24 months.

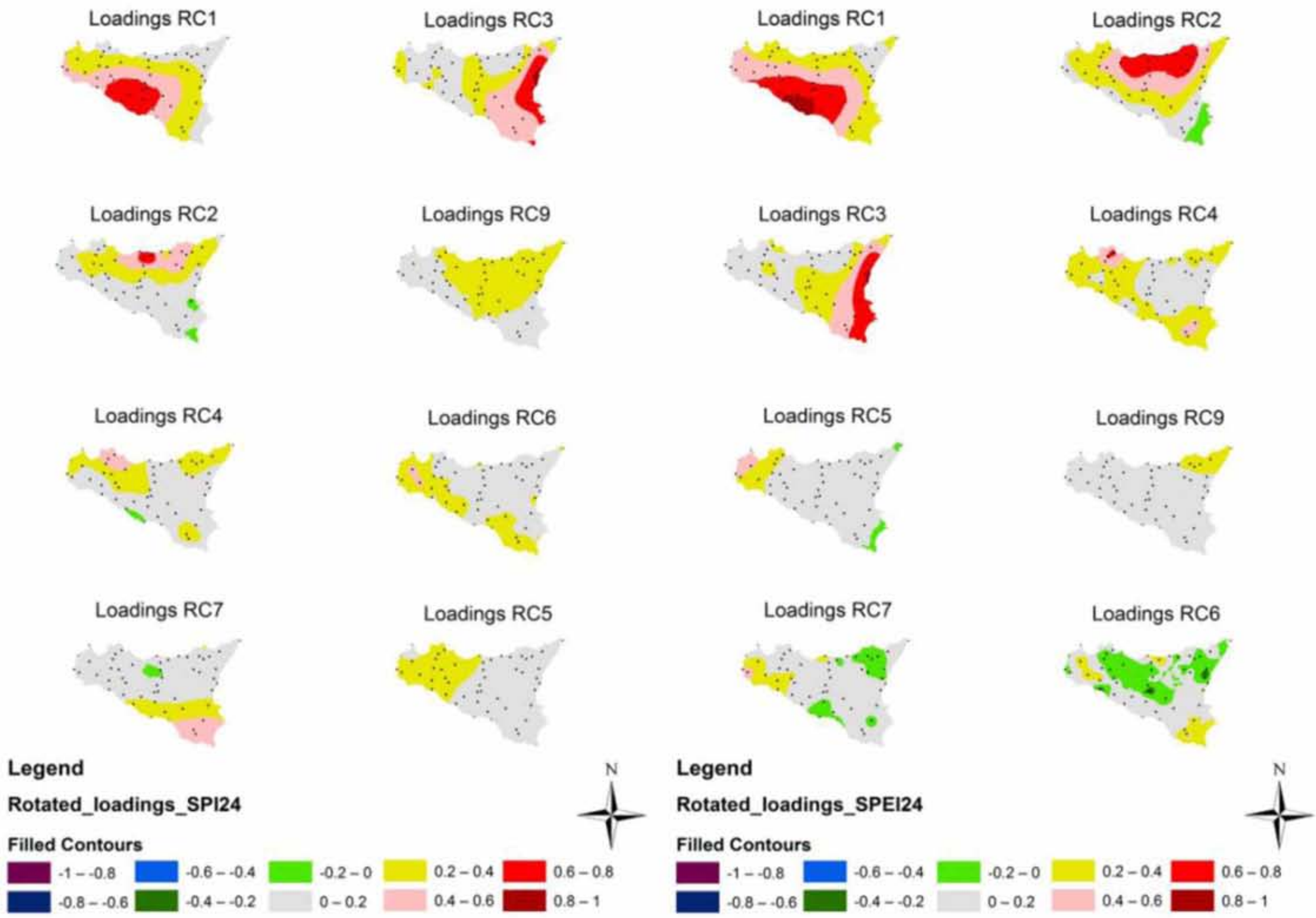

Figure 10 Maps of Sicily representing the loadings of the first 8 rotated principal components for SPI and SPEI indexes for the time scale of 24 months.

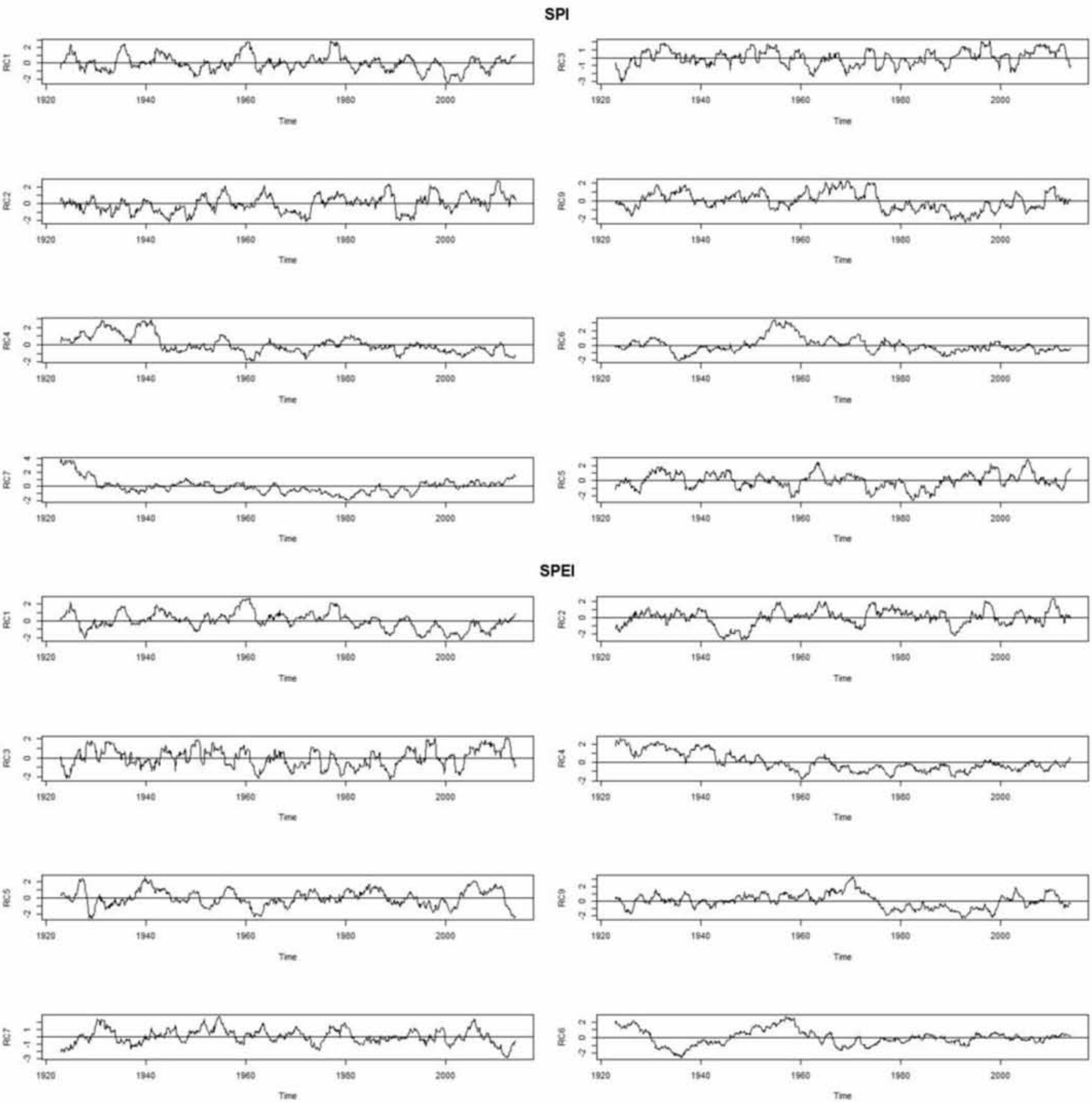

Figure 11 Scores of the first 8 rotated principal components for SPEI and SPI indexes for the time scale of 24 months.

The results for the rest time scales are similar and tables with the variance explained by the components as well as figures are provided in Annex I and II respectively.

Differences are observed however for the time scale of 36 months for the SPI index. More specifically, when the rotation was applied to the principal components, the northern region no longer existed. As mentioned before according to *Vicente-Serrano et al., (2009)* the two indexes may have differences for long time scales when there are increasing trends in temperature. In the northern region (as well as in other parts of the island) there are stations which show significant increasing trends in temperature. Therefore, the incorporation of temperature variability and consequently of PET variability in monitoring droughts can give additional valuable information at least in a local scale. The loadings and the spatial patterns for the time scale of 36 months for the SPI and SPEI indexes are shown in Figure 12. The figures of the loadings for the unrotated case and of the scores for both the unrotated and rotated cases are available in Annex II.

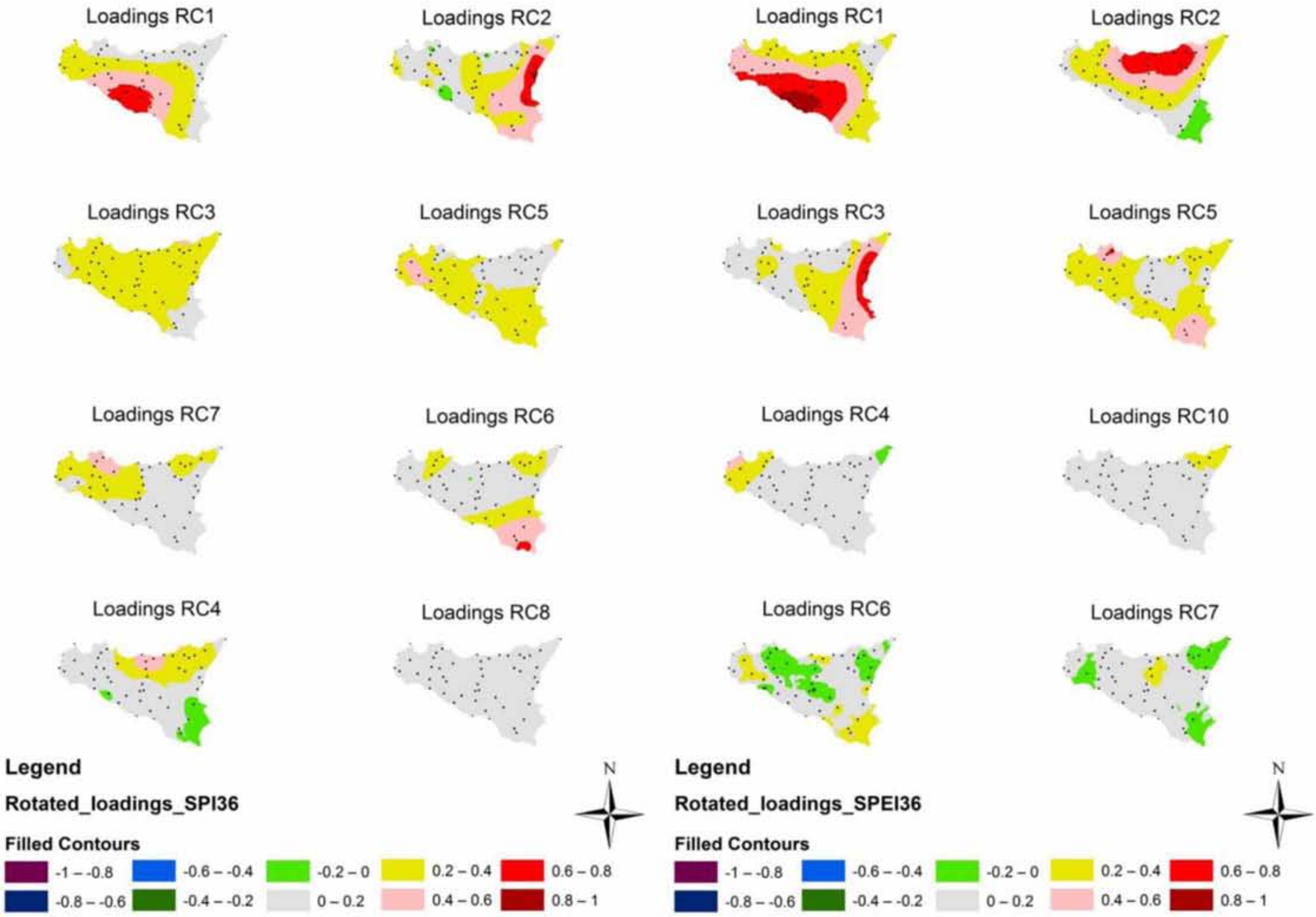

Figure 12 Maps of Sicily representing the loadings of the first 8 rotated principal components for SPI and SPEI indexes for the time scale of 36 months.

4.4 Trend Analysis

The results of the PCA suggest that there are trends in the scores of the first unrotated principal components as well as in the scores of the rotated components. Therefore, it is useful to examine the significance of these trends and make comparisons between the two indexes.

The first unrotated components of the two indexes, which account for most of the variance, show a decreasing tendency towards drier periods starting from the eighties onward. In Figure 13 there are the time series plots of the scores of the first components for the two indexes for all the time scales. Even though, the two indexes follow the same pattern and are quite similar, the p-values of the TFPW-MK test indicate that the general decreasing trend over the island is significant at 95% confidence interval only for SPEI index (in all time scales). Including PET variability in SPEI computation, led to more significant trends. This means that SPEI index may be more appropriate to assess drought conditions in the island. The results are summarized in Table 5.

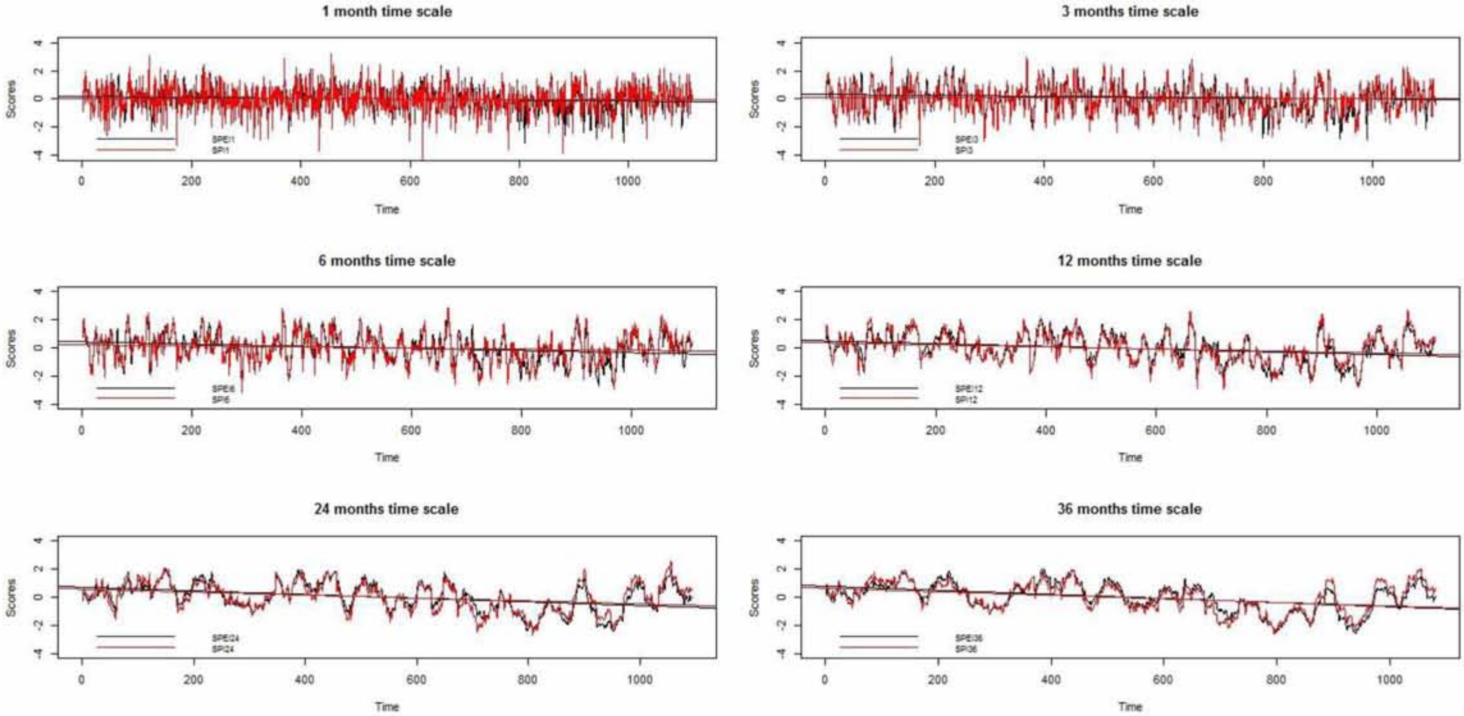

Figure 13 Time series plots of the first principal components of SPI and SPEI index for different time scales.

The significant trends are indicated with bolt characters in Table 5. However, it should be mentioned that as significant trends were considered not only these with p-values lower than 0.05 but also trends with p-values in the range between 0.05 and 0.1. These trends are indicated with italic characters in Table 4. The reason behind this choice is that the limit of 0.05 is defined by men, based on mathematics in order to ease the decision-making procedure. Therefore, strictly mathematically speaking a trend with a p-value=0.06 is not significant, but in a more physically based approach this trend could have some physical meaning.

Table 5 Slopes, intercepts and p-values for the first unrotated principal components of SPI and SPEI indexes for all time scales.

	Slopes	P-Value	Intercept
SPEI1-Times	**-3.29E-04**	**0.002**	**0.196**
SPI1-Times	-7.65E-05	0.39	0.0599
SPEI3-Times	**-5.51E-04**	**0.005**	**0.307**
SPI3-Times	-2.05E-04	0.15	0.124
SPEI6-Times	**-7.58E-04**	**0.019**	**0.436**
SPI6-Times	-3.86E-04	0.11	0.226
SPEI12-Times	**-1.03E-03**	**0.044**	**0.543**
SPI12-Times	-7.06E-04	0.264	0.361
SPEI24-Times	*-1.26E-03*	*0.06*	*0.684*
SPI24-Times	-1.03E-03	0.25	0.565
SPEI36-Times	*-1.46E-03*	*0.07*	*0.782*
SPI36-Times	-1.27E-03	0.2	0.661

Even though the general trend towards drier periods over Sicily Island was found to be statistically significant at 95% confidence interval by SPEI, it seems that the trends in the three regions are not significant in most time scales for both indexes. More specifically, in the northern region (Figure 14) the SPEI index does not show significant trends for any of the time scales while SPI shows only two significant upward trends for the time scales of 12 and 24 months. Similar are the results for the eastern region (Figure 15), where there are no significant trends for the SPEI while for the SPI there is one significant upward trend for the time scale of 1 month. The upward trends of SPI are probably due to the fact that in the eastern and northern region some stations have increasing trends in precipitation. The SPI takes into account only the precipitation variability, therefore the upward trend in precipitation is also reflected in the SPI series. The same (or nearby) stations, however, show also some increasing trends in temperature. The SPEI index which takes account both the temperature and precipitation variability do not show the upward trends of SPI. Finally, for the southern region (Figure 16) the SPEI index shows significant trends in more time scales than SPI. The results for these regions are summarized in Table 6.

Table 6 Slopes, intercepts and p-values for the rotated principal components of SPI and SPEI indexes for all time scales corresponding to the three regions of homogeneous drought conditions.

Time scale	Northern			Eastern			Southern		
	Slopes	P-Val.	Intercept	Slopes	P-Val.	Intercept	Slopes	P-Val.	Intercept
SPEI1	3.79E-05	0.74	-2.69E-03	-7.67E-05	0.49	-1.14E-02	**-7.71E-04**	**1.4E-09**	**4.32E-01**
SPI1	-4.52E-05	0.63	-1.68E-02	**2.53E-04**	**0.02**	**-2.09E-01**	-1.00E-01	0.39	1.07E-01
SPEI3	1.32E-04	0.83	-7.51E-02	-3.67E-05	0.76	-2.94E-02	**-8.8E-04**	**5.9E-04**	**4.9E-01**
SPI3	2.84E-05	0.64	-1.21E-02	3.15E-04	0.15	2.43E-01	-1.93E-05	9.02E-01	-7.78E-03
SPEI6	2.19E-04	0.5	-1.72E-01	-3.41E-05	0.71	-2.73E-02	**-9.57E-04**	**0.02**	**5.45E-01**
SPI6	1.52E-04	0.72	-6.36E-02	1.83E-04	0.92	-1.53E-01	-4.04E-04	0.28	2.22E-01
SPEI12	3.37E-04	0.28	-1.5E-01	-1.99E-04	0.61	8.31E-02	-1.02E-03	0.16	6.02E-01
SPI12	**8.77E-04**	**0.023**	**-5.2E-01**	1.17E-04	0.87	-7.72E-02	-7.84E-04	0.22	4.34E-01
SPEI24	3.18E-04	0.59	-5.69E-02	9.18E-05	0.90	-6.38E-02	*-1.18E-03*	*0.07*	*6.67E-01*
SPI24	*1.02E-03*	*0.06*	*-5.38E-01*	5.9E-04	0.48	-3.08E-01	-4.61E-04	0.25	2.12E-01
SPEI36	2.24E-04	0.96	6.46E-03	2.29E-04	0.41	-7.9E-02	-1.38E-03	0.32	7.63E-01
SPI36	-	-	-	7.81E-04	0.08	-3.71E-01	-4.53E-04	0.67	9.68E-02

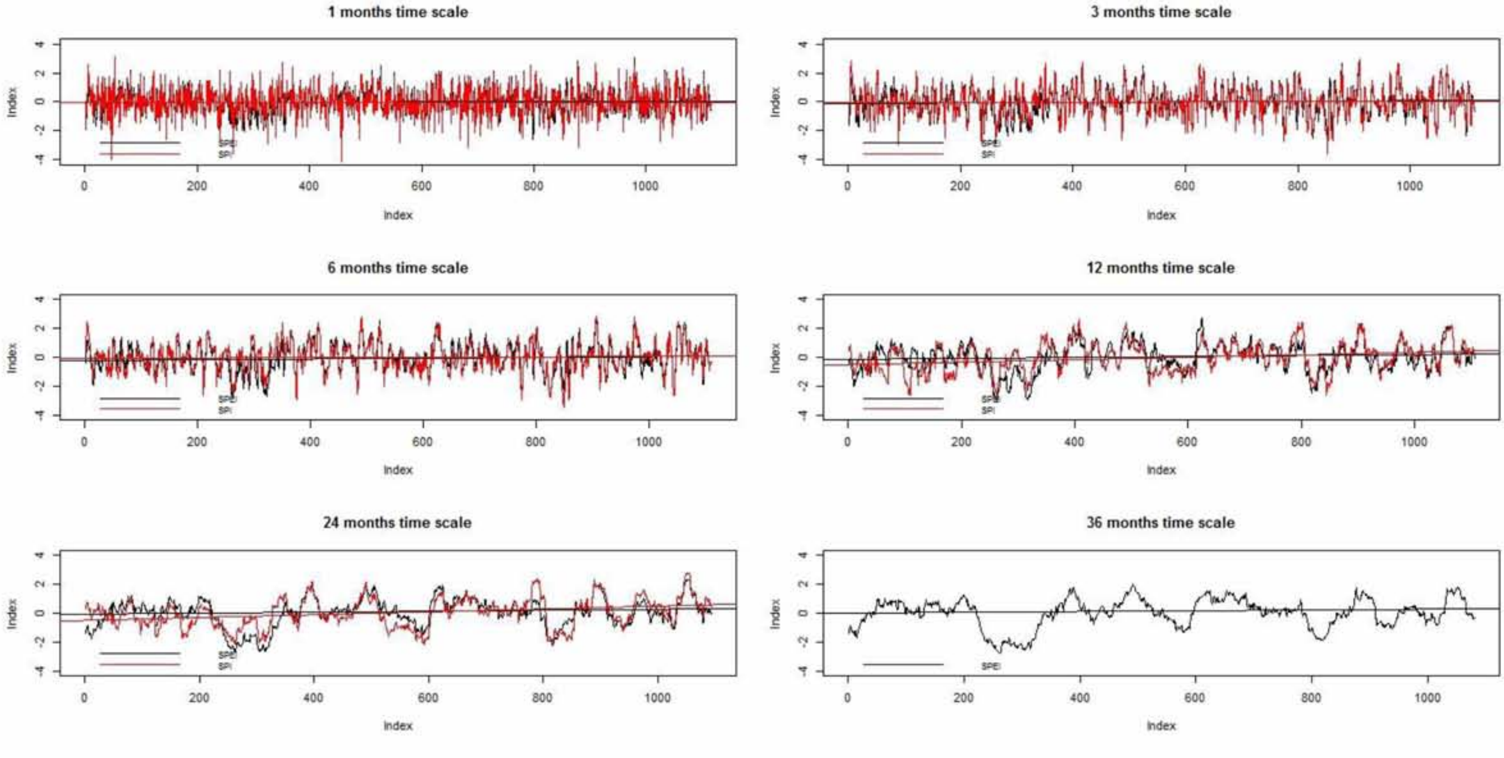

Figure 14 Time series scores and trends of the rotated principal components corresponding to the northern region of SPEI and SPI indices for various time scales.

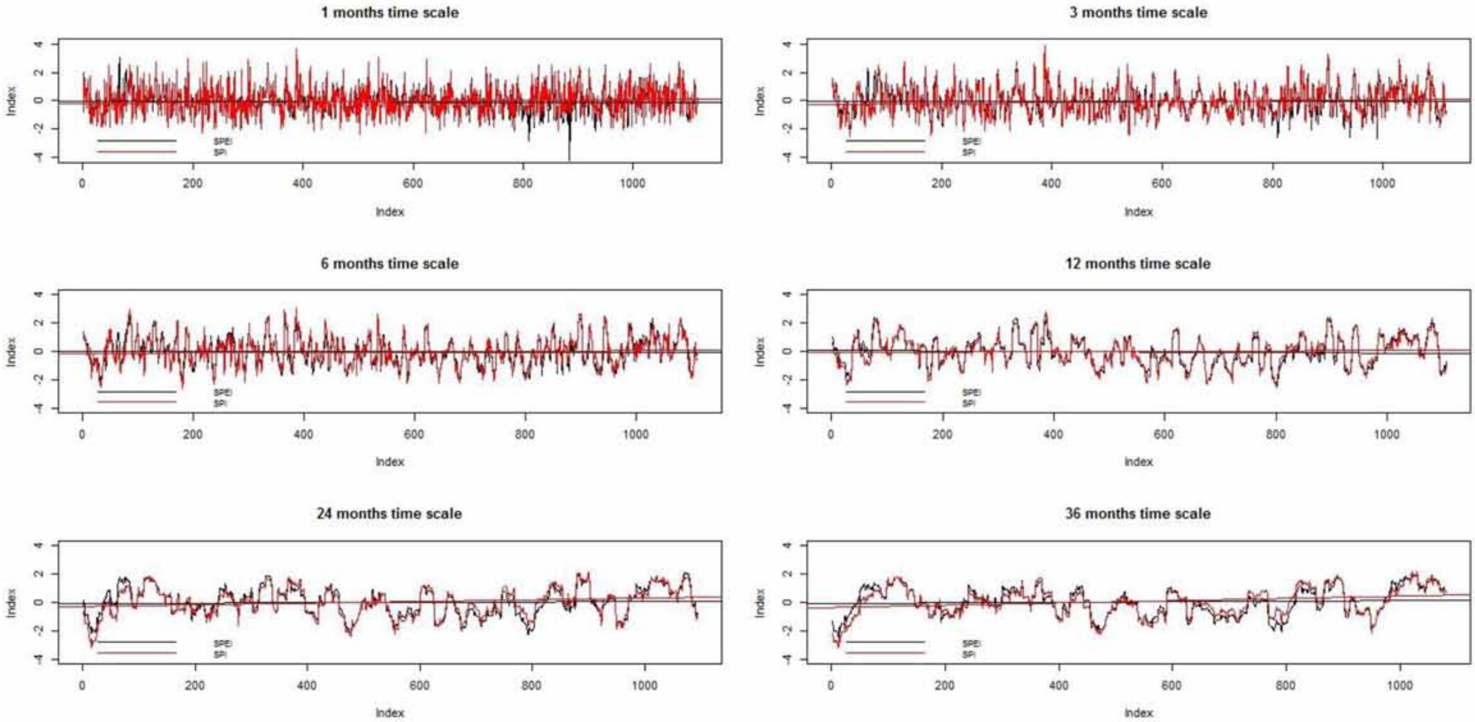

Figure 15 Time series scores and trends of the rotated principal components corresponding to the eastern region of SPEI and SPI indices for various time scales.

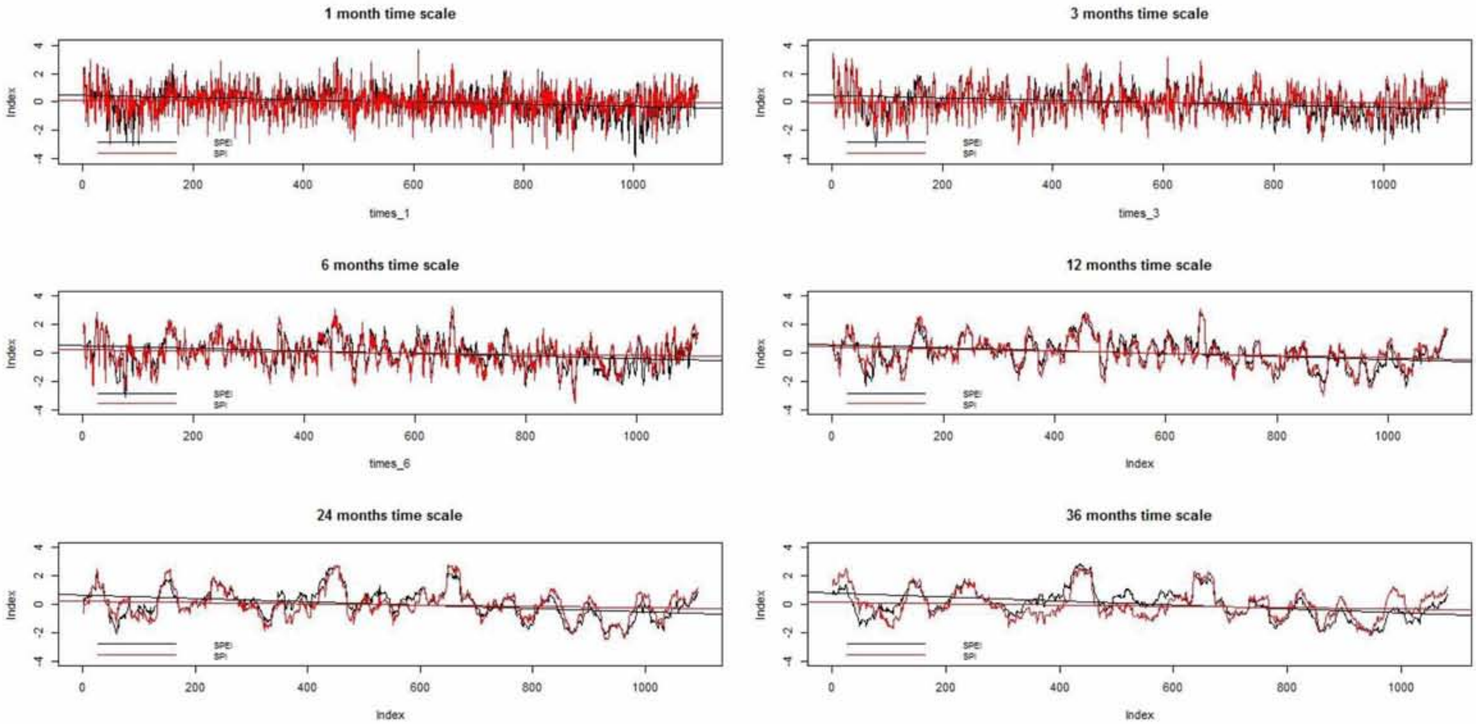

Figure 16 Time series scores and trends of the rotated principal components corresponding to the southern region of SPEI and SPI indices for various time scales.

4.5 Run sum analysis method

During the period 1980-2013, the most severe drought events occurred. Therefore, a more detailed analysis on how these events were captured by the two indices was performed. The characteristics of these events were extracted using the run sum analysis method and are shown in Table 7 and 8. The analysis was performed for the time scales of 12 and 24 months because in longer time scales the temporal variability of SPEI and SPI indexes is smoothed allowing for the major patterns to emerge from the noise. Thus, it is easier to make comparisons between the two indexes in these time scales.

In Figures 17 and 18, there are plots of the scores of the first principal components of the two indices for the time scales of 12 and 24 months respectively.

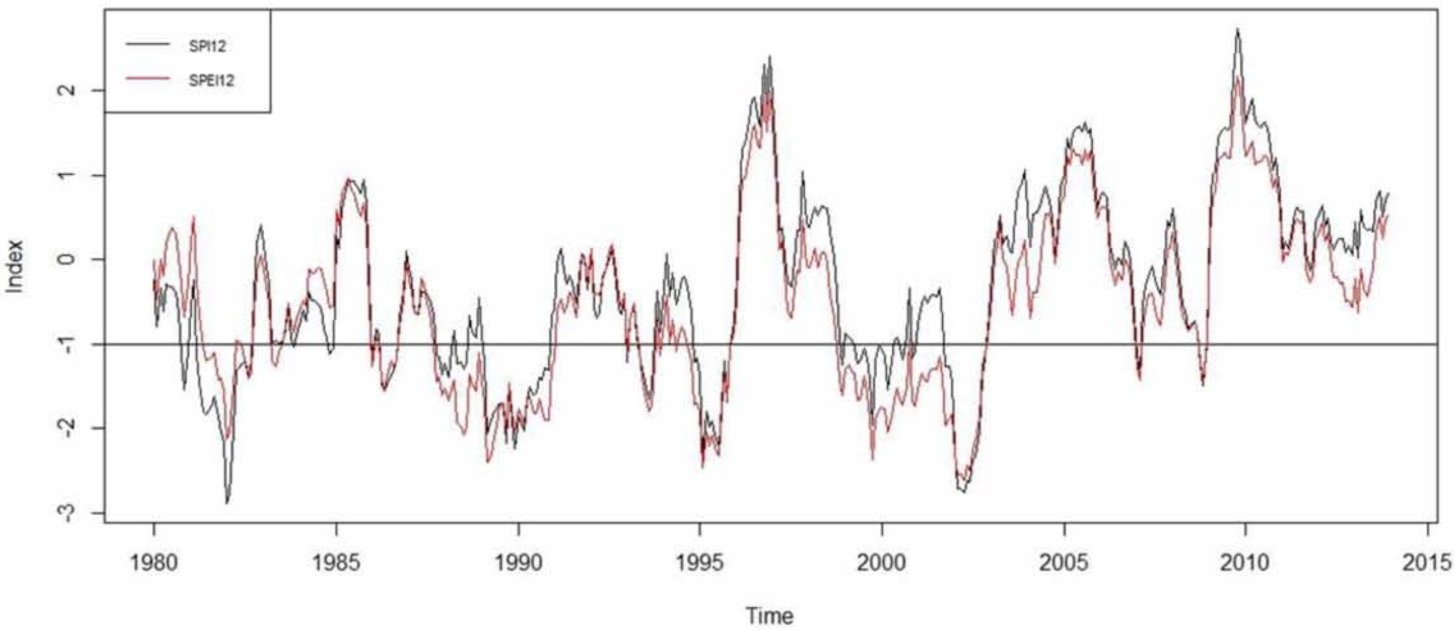

Figure 17 Scores time series plots of the first principal components of the SPEI and SPI indexes for the period 1980-2013 for the time scale of 12 months.

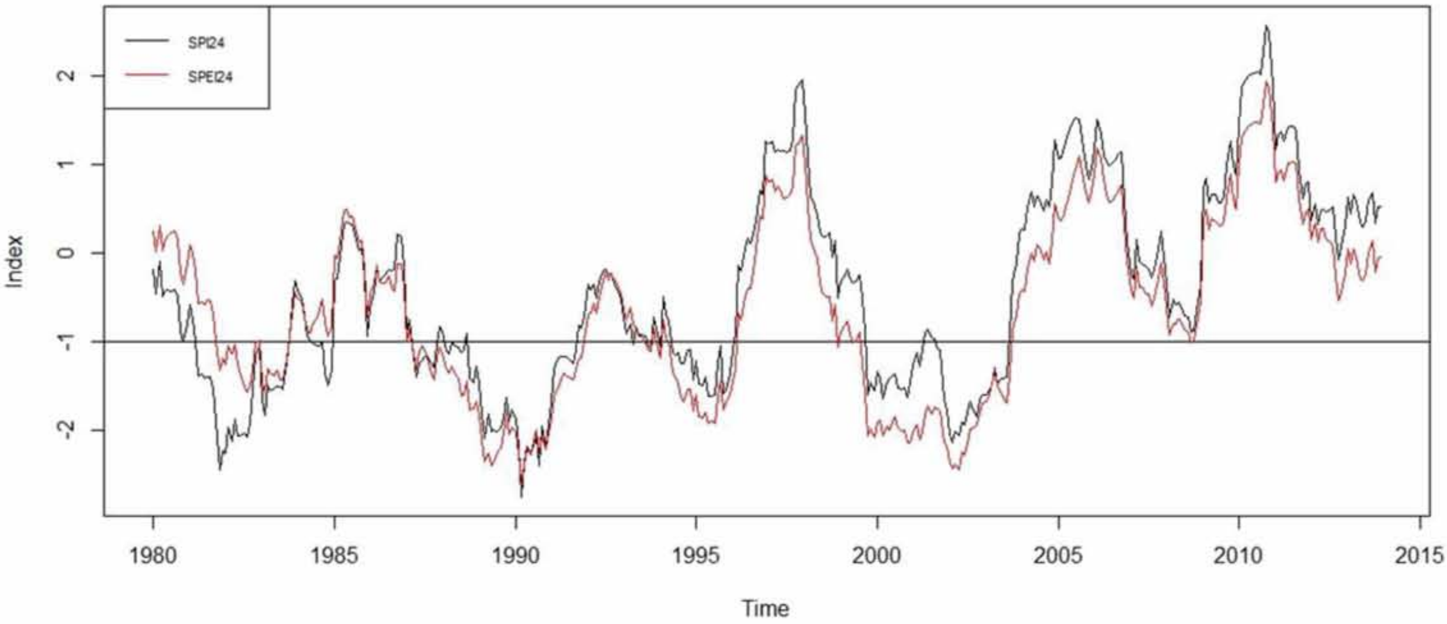

Figure 18 Scores time series plots of the first principal components of the SPEI and SPI indexes for the period 1980-2013 for the time scale of 24 months.

Even though the two indexes follow the same pattern and were both able to capture the severe drought events, the magnitudes, severities and onsets of some events appear to be different. The results suggest that SPI overestimates the wet periods and underestimates some of the severe drought events comparing to SPEI. Two, characteristic examples are during the periods 1987-91 and 1998-2002. These differences in magnitudes and onset may be due to the fact that SPI does not take into account the potential evapotranspiration variability. Based only on precipitation variability, SPI may be influenced by some peaks in the precipitation series leading to overestimation of wet periods or underestimation of drought periods. Another possible reason is that maybe during these events the evapotranspiration rates were quite high favoring drought conditions in the island. The SPEI index which incorporates the PET variability identifies drought events with bigger magnitudes. Concerning the onset of the severe drought events it seems that there are no big differences between the two indexes except for the events in early eighties where it is clear that SPI captures the onset of the drought events earlier than SPEI. During this period, the evapotranspiration could be quite low leading to a delayed onset of the drought event. Moreover, examining the characteristics of the events in Tables 7 and 8 it should be mentioned that SPEI index identifies fewer events but with longer average duration and with larger average volume of deficit.

Table 7 Characteristics (Volume, Duration and End Date) of drought events for the period of 1980-2013 for the time scale of 12 months

	SPI 12			SPEI12	
Volume	Duration	End Date	Volume	Duration	End Date
0.745	3	Dec-80	4.779	11	Mar-82
13.697	19	Sep-82	1.024	4	Sep-82
0.035	1	Nov-83	0.578	4	Jul-83
0.154	2	Dec-84	0.266	1	Jan-86
0.237	1	Jan-86	1.982	6	Sep-86
2.372	6	Sep-86	28.863	40	Jan-91
1.304	6	Mar-88	0.107	1	Jan-93
0.952	4	Aug-88	2.820	6	Oct-93
15.609	22	Nov-90	0.137	1	Dec-93
0.215	1	Jan-93	0.086	1	May-94
2.012	5	Sep-93			
8.684	13	Nov-95			
0.247	1	Dec-98			
3.209	13	Apr-00			
0.216	2	Aug-00			
0.272	2	Dec-00			
14.902	14	Nov-02			
0.487	2	Feb-07			
0.747	2	Nov-08			
Average Volume	Average Duration	Number of events	Average Volume	Average Duration	Number of events
5.9	9.6	15	3.5	6.3	10

Table 8 Characteristics (Volume, Duration and End Date) of drought events for the period of 1980-2013 for the time scale of 12 months

	SPI 24			SPEI 24	
Volume	Duration	End Date	Volume	Duration	End Date
21.25	30	Sep-83	3.65	14	Nov-82
0.12	3	Aug-84	3.47	9	Sep-83
1.16	3	Dec-84	40.37	57	Nov-91
1.81	9	Nov-87	0.20	3	Oct-93
0.24	2	Mar-88	0.20	2	Jan-94
0.32	4	Aug-88	14.09	22	Feb-96
28.08	36	Sep-91	0.07	1	Dec-98
0.03	1	Apr-93	0.01	1	May-99
0.11	2	Oct-93	45.41	50	Sep-03
0.08	1	Jan-94	0.02	1	Sep-08
6.80	21	Jan-96			
8.05	19	Apr-01			
15.73	24	Aug-03			
Average Volume	Average Duration	Number of events	Average Volume	Average Duration	Number of events
6.5	11.9	13	10.8	16	10

5. Conclusions

The objective of this study was to compare the ability of SPI and SPEI indexes to monitor droughts as well as to describe its spatial patterns over Sicily Island. Therefore, in this study an analysis of drought variability in Sicily has been carried out using SPI and SPEI indexes calculated for the time scales of 1, 3, 6, 12, 24 and 36 months in 50 meteorological stations.

The correlation analysis showed that the two indices are strongly correlated in all time scales as expected. The strongest correlation was observed for the time scale of 12 months. The correlation analysis also confirmed what *Vicente-Serrano et al., (2009)* reported, that the two indexes may have lower correlation in longer time scales (here 36 months) when there are significant trends in temperature in some stations.

Examining the results of PCA it can be concluded that there is a common tendency towards drier periods from the eighties onward and the main spatial patterns of SPI and SPEI variability characterize Sicily uniformly. Even though the general drought pattern existing over the island is captured by both indexes the proportions of variance by the leading principal components of the two indexes is different and more specifically higher in the case of SPEI. This means that the sensitivity of the two indexes to drought variability differs and therefore the incorporation of the PET variability in drought monitoring may have a significant role.

This aspect is also supported examining the results after the varimax rotation was applied to the principal components. The results suggest that there are three regions of homogeneous drought conditions, namely, southern, eastern and northern Sicily. However, the SPI index misses the northern region for long time scales and more specifically for the time scale of 36 months. This does not happen with the SPEI index. Concerning the different time scales used in this study, it can be concluded that the spatial patterns of drought variability are more or less the same but the relative variance explained by the components in each time scale is different, meaning that different mitigation measures should be considered in each case.

The general trend towards drier periods starting from the eighties onward appears to be significant (for all the time scales) only when the analysis was based on the SPEI index. Moreover, in a local scale the SPI index seems to be influenced by the increasing trends in the precipitation existing in some stations in northern and eastern region reflecting these trends also in drought conditions. This does not happen with the SPEI index. Moreover, the SPEI index identifies significant decreasing trends in the southern region where there are decreasing trends in precipitation and temperature in many stations. On the other hand, SPI does not show similar behavior in this region. Therefore, it can be concluded that temperature and consequently PET variability may have a significant role in the analysis of drought variability and in the ability of drought indices to capture trends.

Finally, the investigation of the severe drought events during the period 1980-2013 suggests that a drought index that takes account PET variability like SPEI may give more valuable information about the magnitude and severity of the events but not for the onset of these events.

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Annex I

1 month time scale:

Table I. 1 Proportion of Variance explained for each of the 8 principal components for the unrotated and rotated case for the time scale of 1 month.

SPI index				SPEI index		
Unrotated Principal Components	Variance (%)	Rotated Principal Components	Varimax (%)	Variance (%)	Rotated Principal Components	Varimax (%)
PC1	54.7	RC2	18.5	63	RC2	20
PC2	6.6	RC1	17.9	6.3	RC3	14.2
PC3	4.8	RC4	14.6	5.1	RC4	13.2
PC4	2.4	RC3	12.1	2.8	RC5	12.9
PC5	1.6	RC8	3	1.7	RC1	10.7
PC6	1.4	RC7	2.6	1.5	RC7	5.4
PC7	1.2	RC5	2.5	1.3	RC6	3.6
PC8	1.1	RC6	1.9	1.1	RC10	1.9

3 months' time scale:

Table I. 2 Proportion of Variance explained for each of the 8 principal components for the unrotated and rotated case for the time scale of 3 months.

SPI index				SPEI index		
Unrotated Principal Components	Variance (%)	Rotated Principal Components	Varimax (%)	Variance (%)	Rotated Principal Components	Varimax (%)
PC1	53.5	RC2	17.9	58.5	RC2	19.4
PC2	7.8	RC1	15.7	7.2	RC1	19.3
PC3	5.5	RC4	13.6	5.5	RC3	13.4
PC4	2.9	RC3	13.5	3.1	RC4	12
PC5	1.8	RC9	6	2	RC7	6.2
PC6	1.6	RC10	3.1	1.6	RC5	3.6
PC7	1.6	RC5	2.8	1.4	RC6	2.9
PC8	1.4	RC6	2.5	1.3	RC9	2.6

6 months' time scale:

Table I. 3 Proportion of Variance explained for each of the 8 principal components for the unrotated and rotated case for the time scale of 6 months.

		SPI index			SPEI index	
Unrotated Principal Components	Variance (%)	Rotated Principal Components	Varimax (%)	Variance (%)	Rotated Principal Components	Varimax (%)
PC1	50.4	RC1	22.3	54.8	RC1	21.7
PC2	8.3	RC2	16	7.4	RC2	18.2
PC3	6.1	RC3	15.4	6.1	RC3	14.7
PC4	3	RC4	7.7	3.3	RC4	9.7
PC5	2.2	RC5	4.8	2.5	RC6	4.7
PC6	1.9	RC6	3	1.9	RC9	3.7
PC7	1.8	RC10	2.8	1.6	RC10	2.5
PC8	1.7	RC8	2.3	1.5	RC5	2.5

36 months' time scale:

Table I. 4 Proportion of Variance explained for each of the 8 principal components for the unrotated and rotated case for the time scale of 36 months.

		SPI index			SPEI index	
Unrotated Principal Components	Variance (%)	Rotated Principal Components	Varimax (%)	Variance (%)	Rotated Principal Components	Varimax (%)
PC1	44.4	RC1	14.6	52.9	RC1	27.5
PC2	7.3	RC2	11.8	8.2	RC2	17.5
PC3	6.9	RC3	11.4	7.4	RC3	11.6
PC4	5.3	RC5	9.4	4.2	RC5	10.9
PC5	4.7	RC7	8.1	4	RC4	4.1
PC6	3.7	RC6	7.6	2.9	RC10	4
PC7	3.1	RC4	7.2	2.2	RC6	3.4
PC8	2.8	RC8	4.4	2	RC7	3

Anex II

Principal components analysis figures:

1 month time scale:

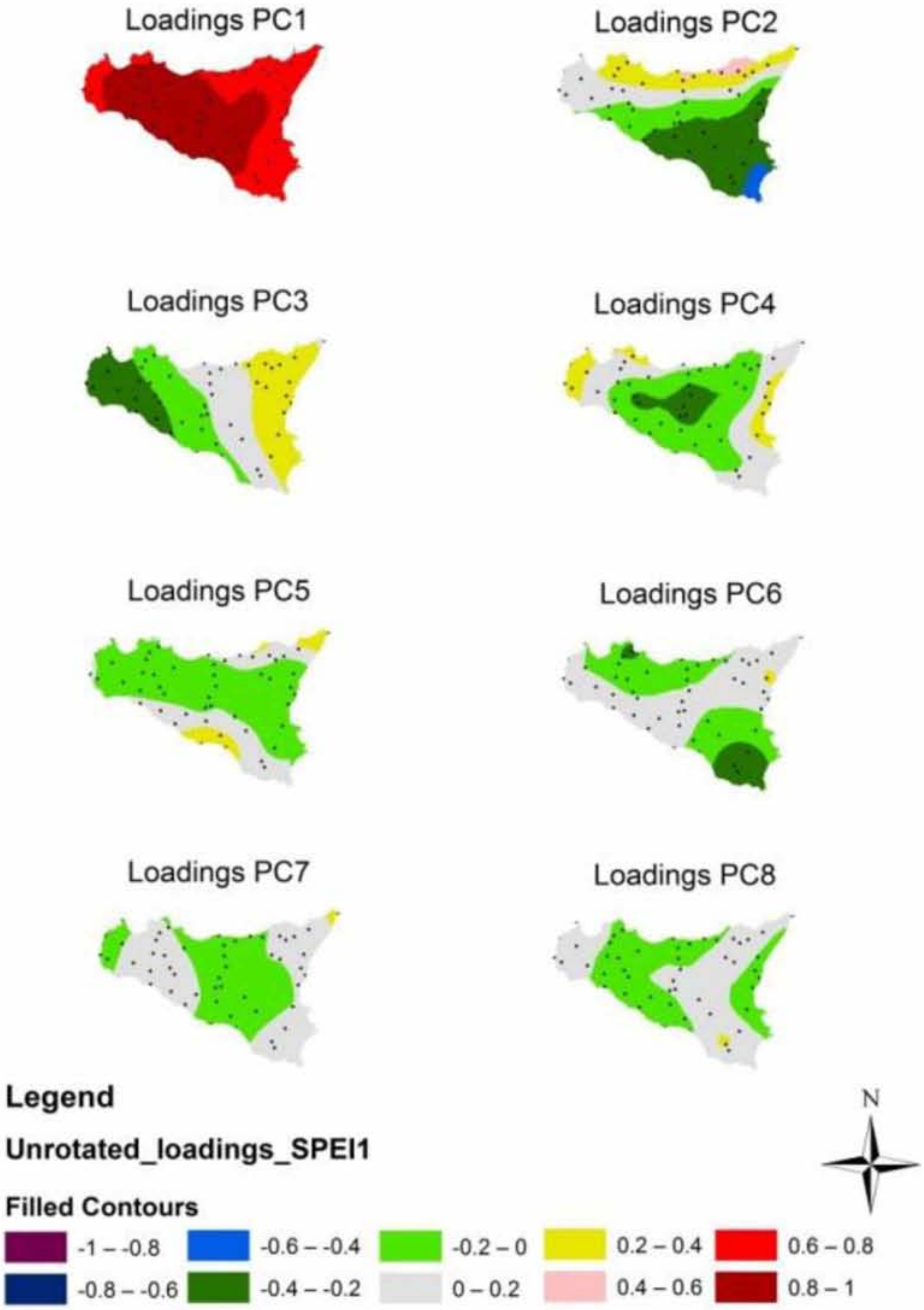

Figure II. 1 Loadings of first 8 unrotated principal components for SPEI index of 1 month time scale.

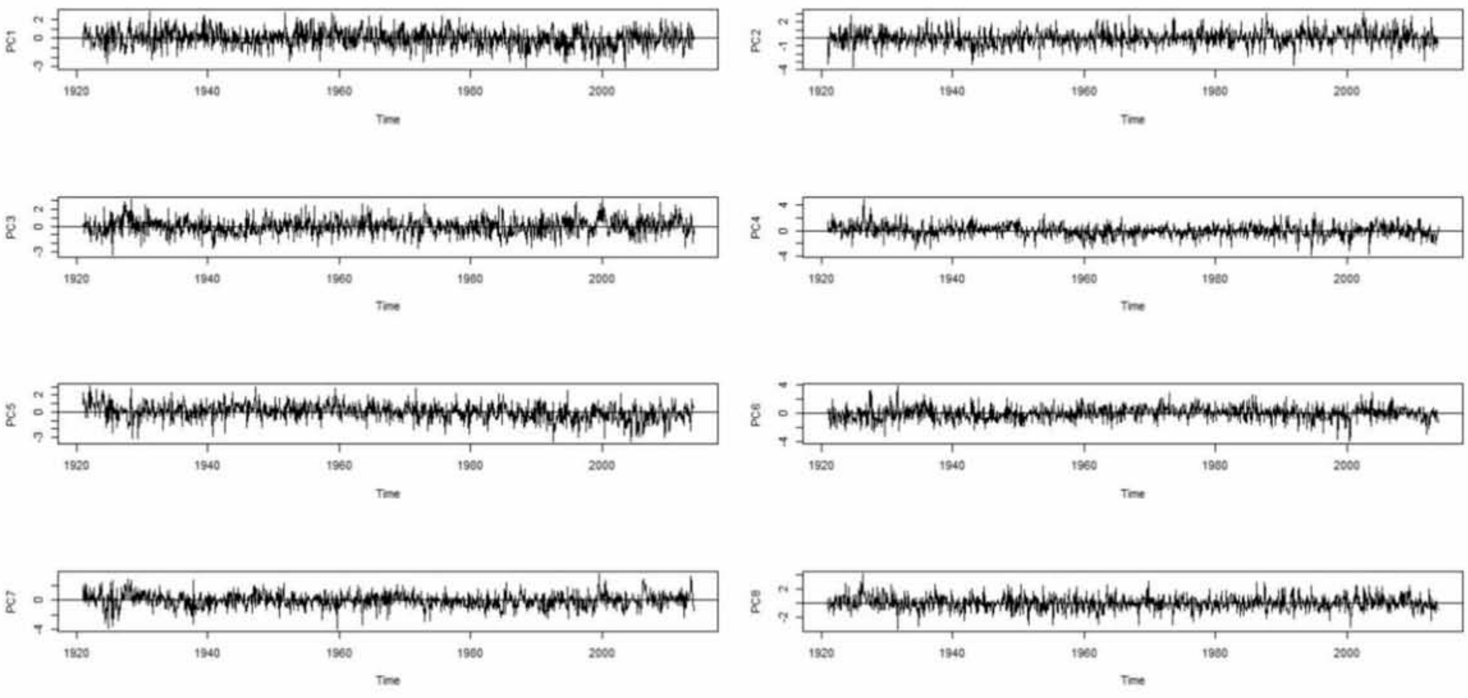

Figure II. 2 First 8 unrotated scores for the period 1921-2013, based on SPEI index of 1 month time scale.

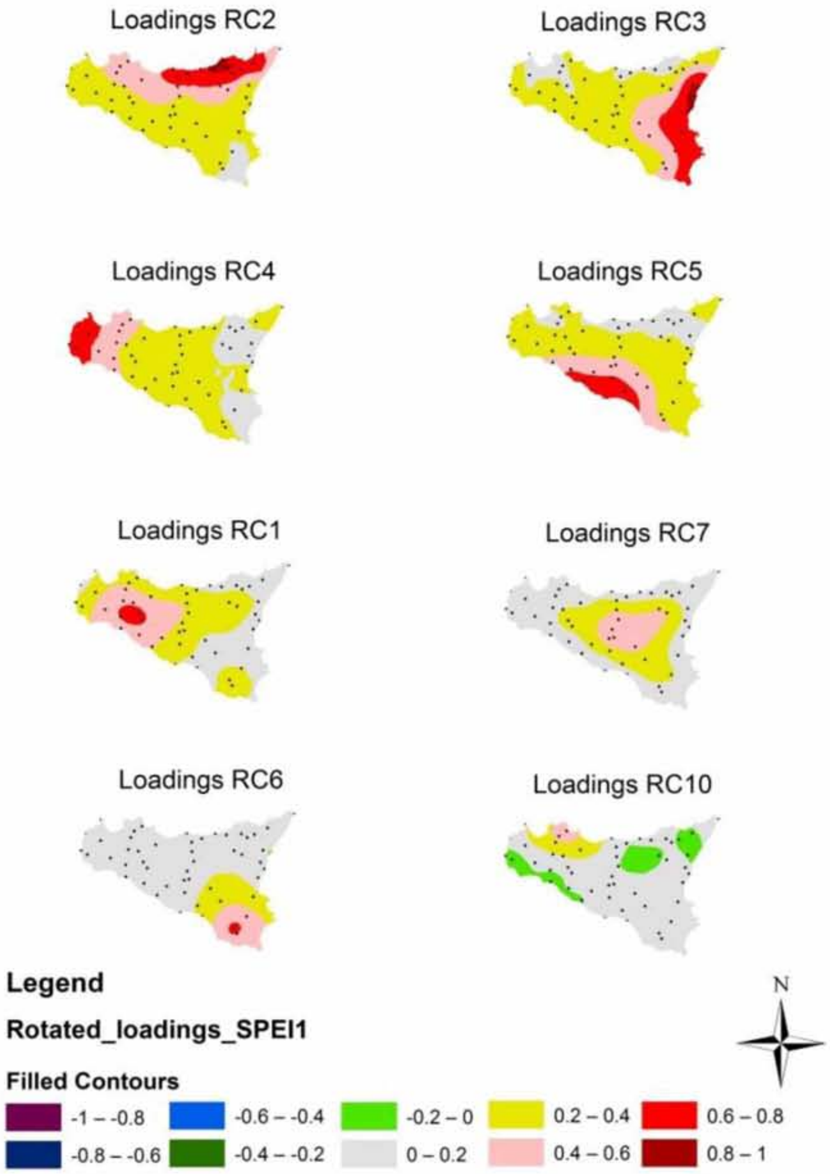

Figure II. 3 Loadings of first 8 rotated principal components for SPEI index of 1 month time scale.

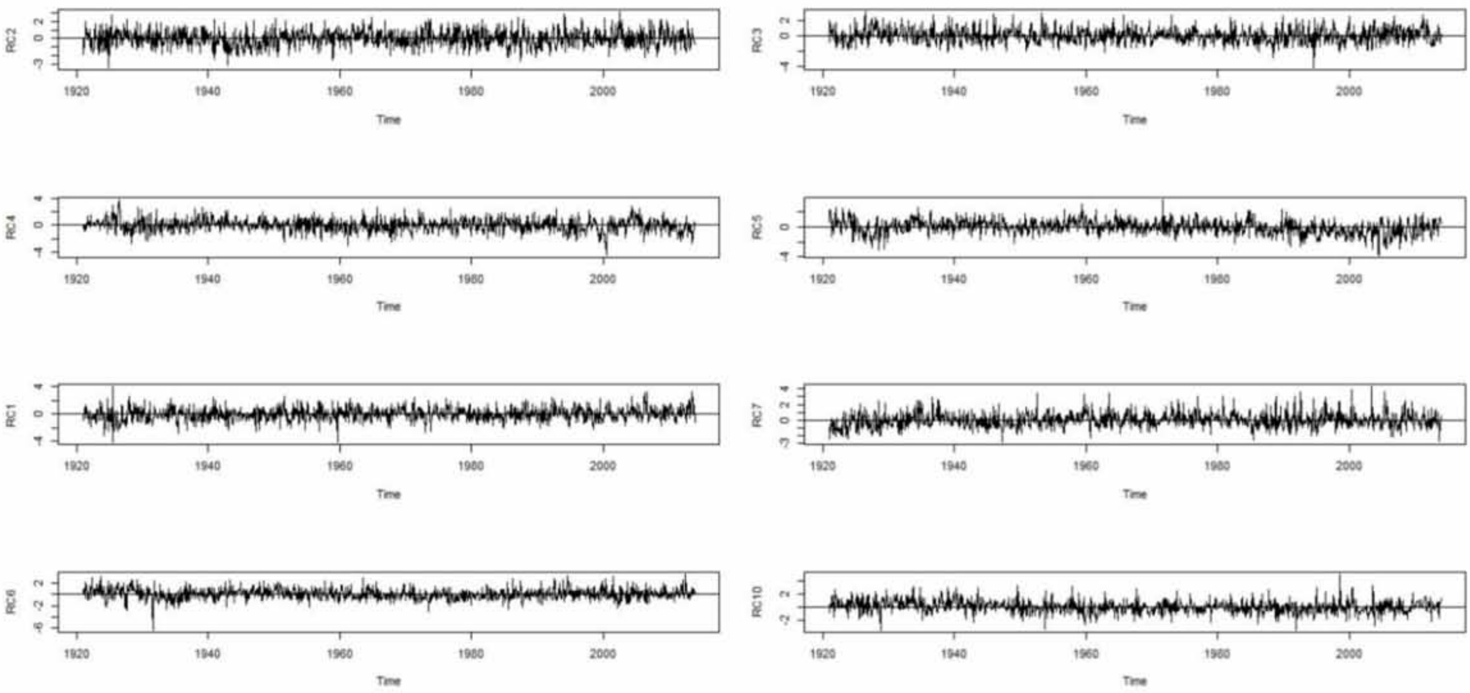

Figure II. 4 First 8 rotated scores for the period 1921-2013, based on SPEI index of 1 month time scale.

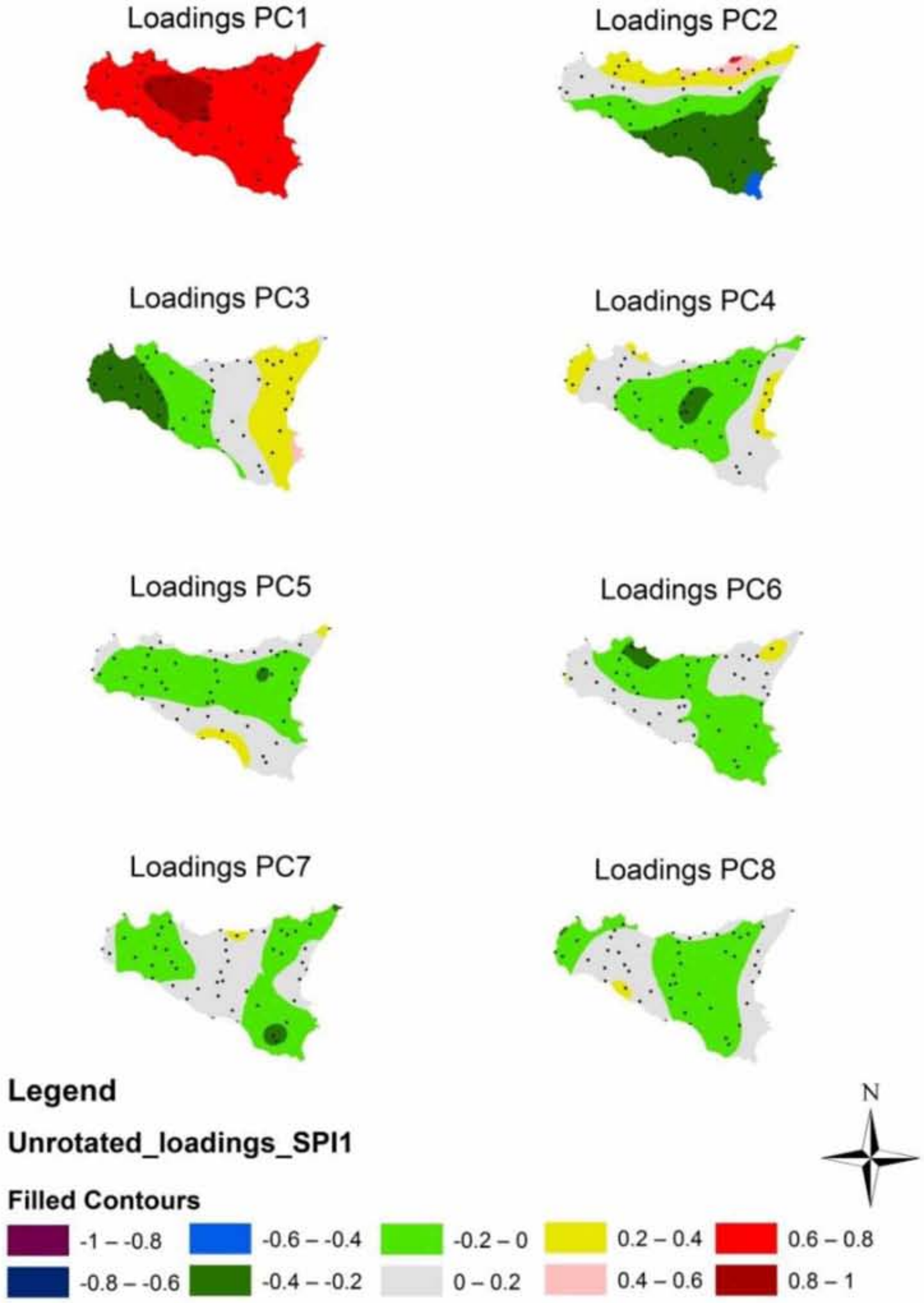

Figure II. 5 Loadings of first 8 unrotated principal components for SPI index of 1 month time scale.

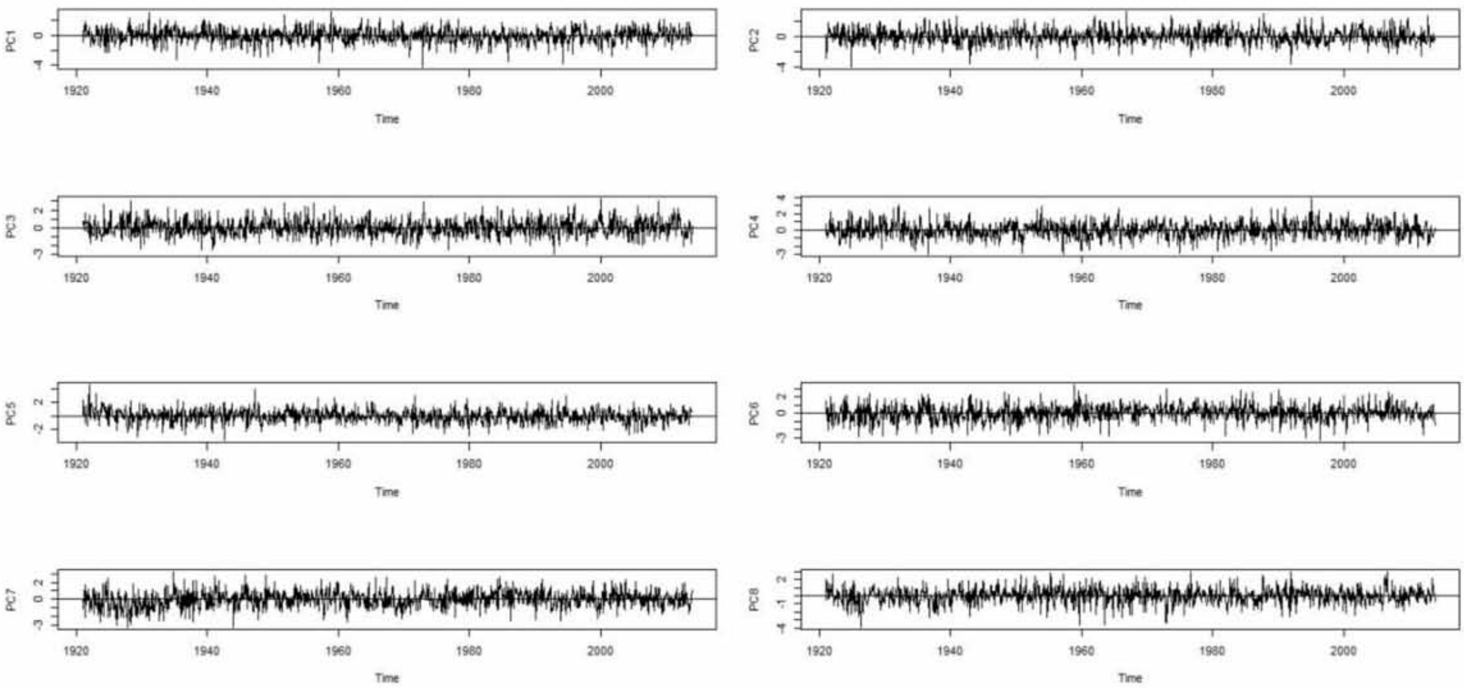

Figure II. 6 First 8 unrotated scores for the period 1921-2013, based on SPI index of 1 month time scale.

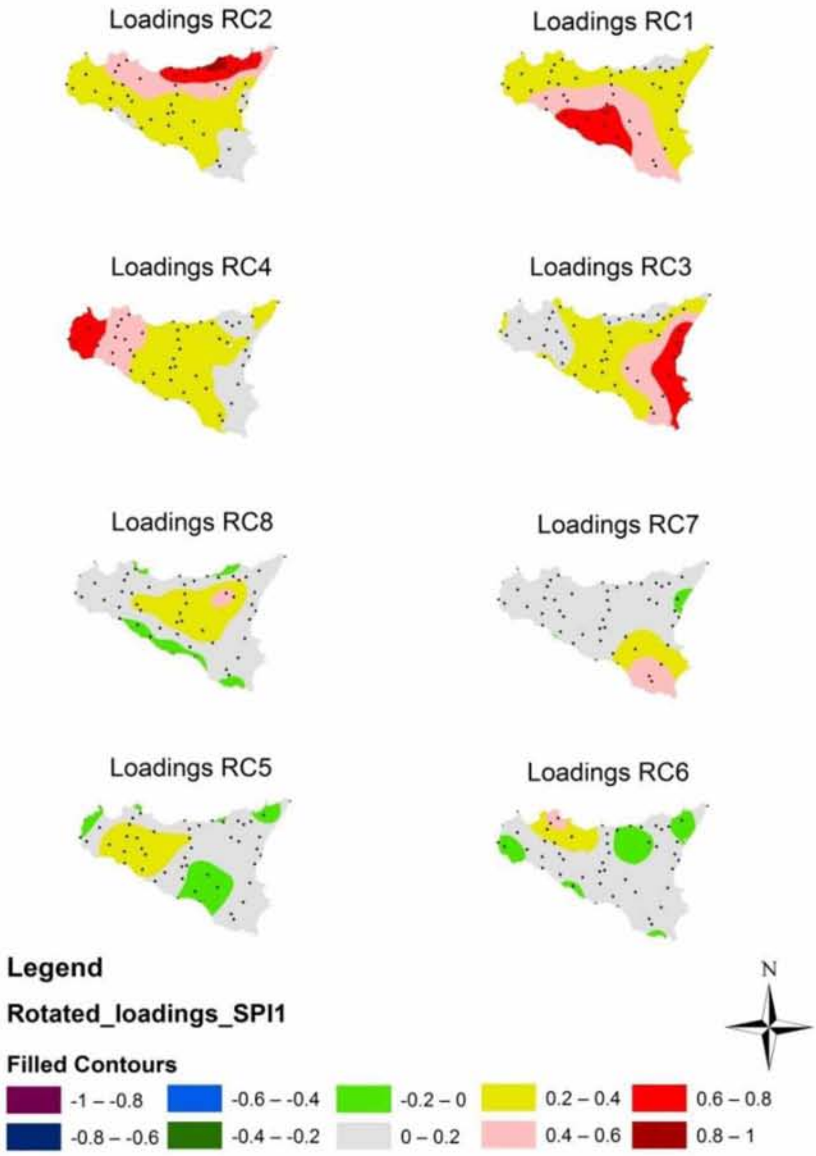

Figure II. 7 Loadings of first 8 rotated principal components for SPI index of 1 month time scale.

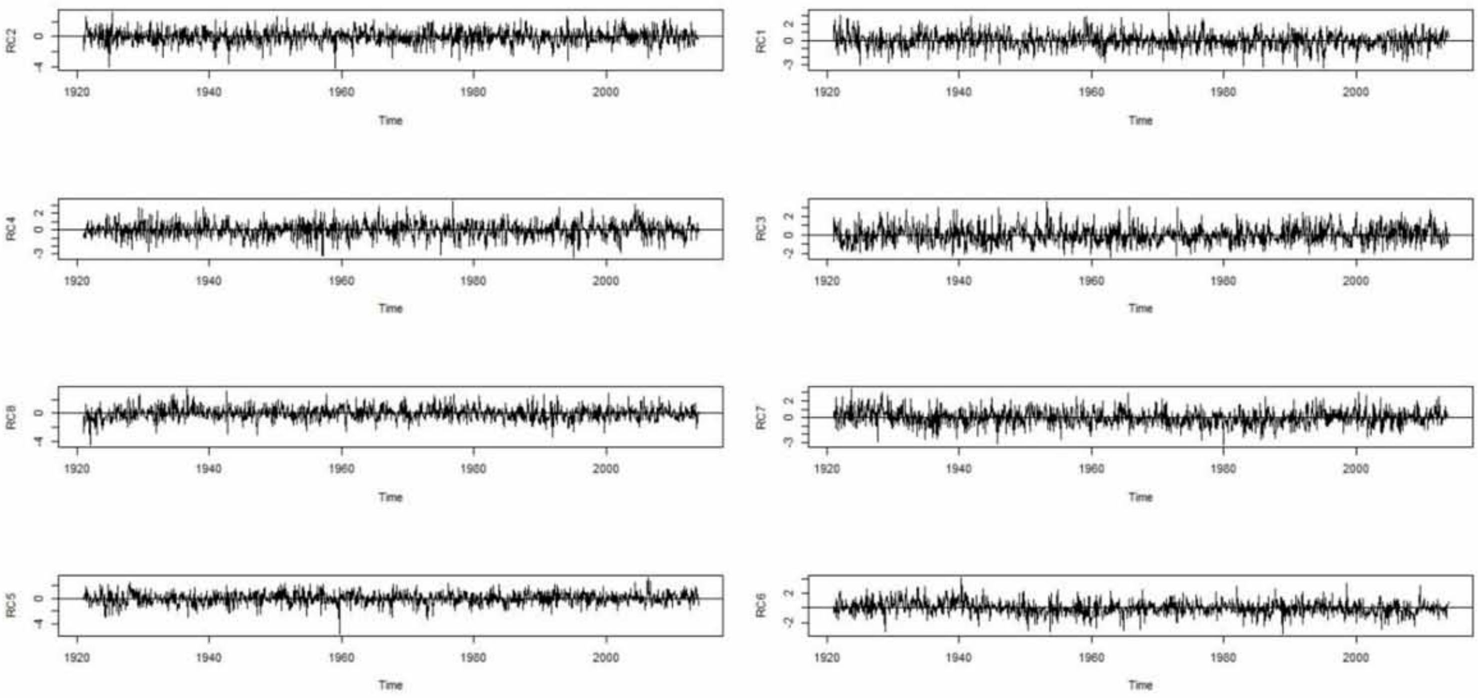

Figure II. 8 First 8 rotated scores for the period 1921-2013, based on SPI index of 1 month time scale.

3 months time scale:

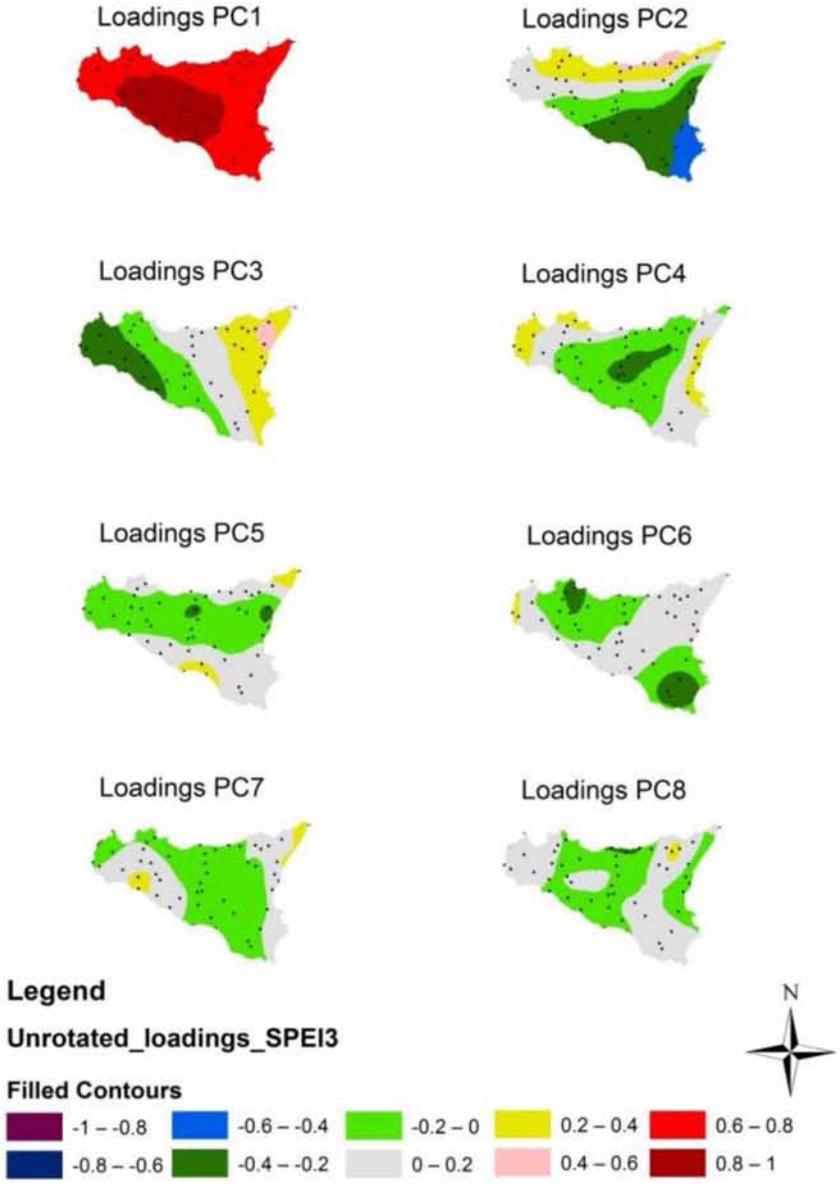

Figure II. 9 Loadings of first 8 unrotated principal components for SPEI index of 3 months' time scale.

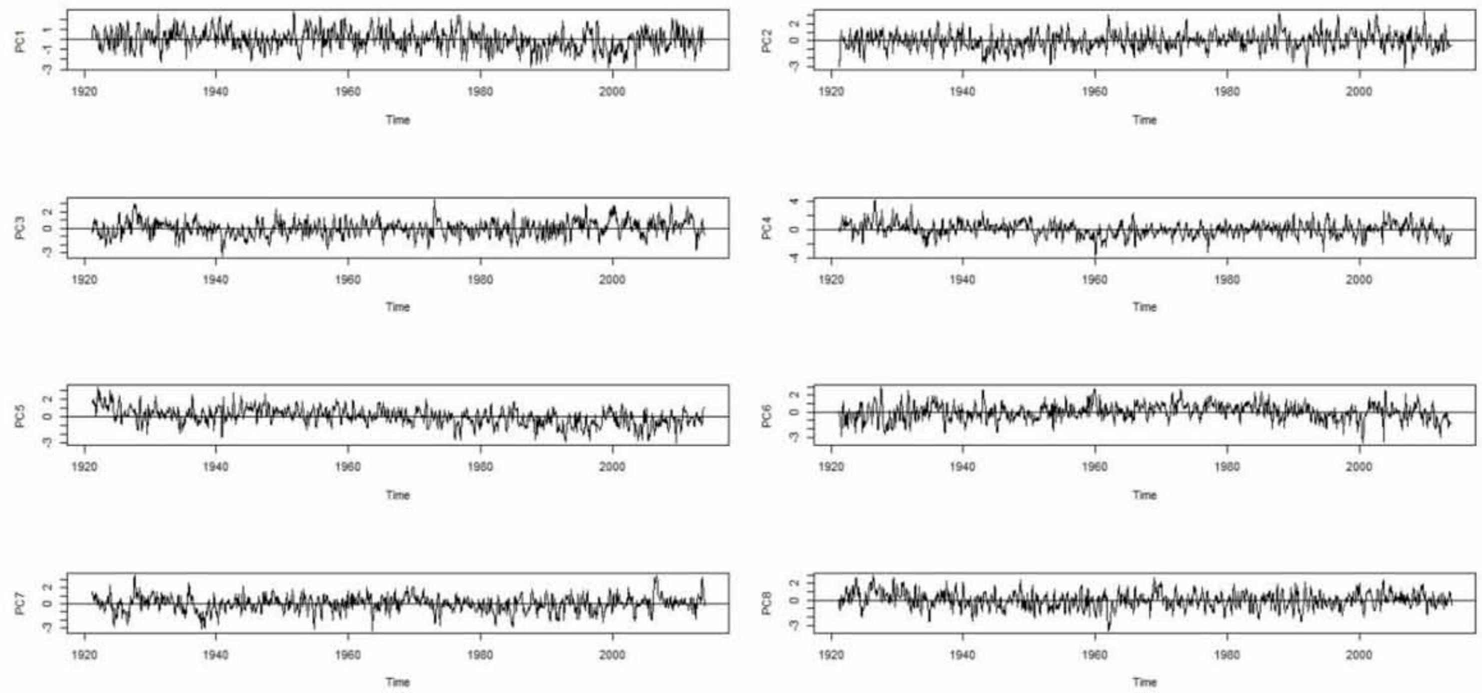

Figure II. 10 First 8 unrotated scores for the period 1921-2013, based on SPEI index of 3 months' time scale.

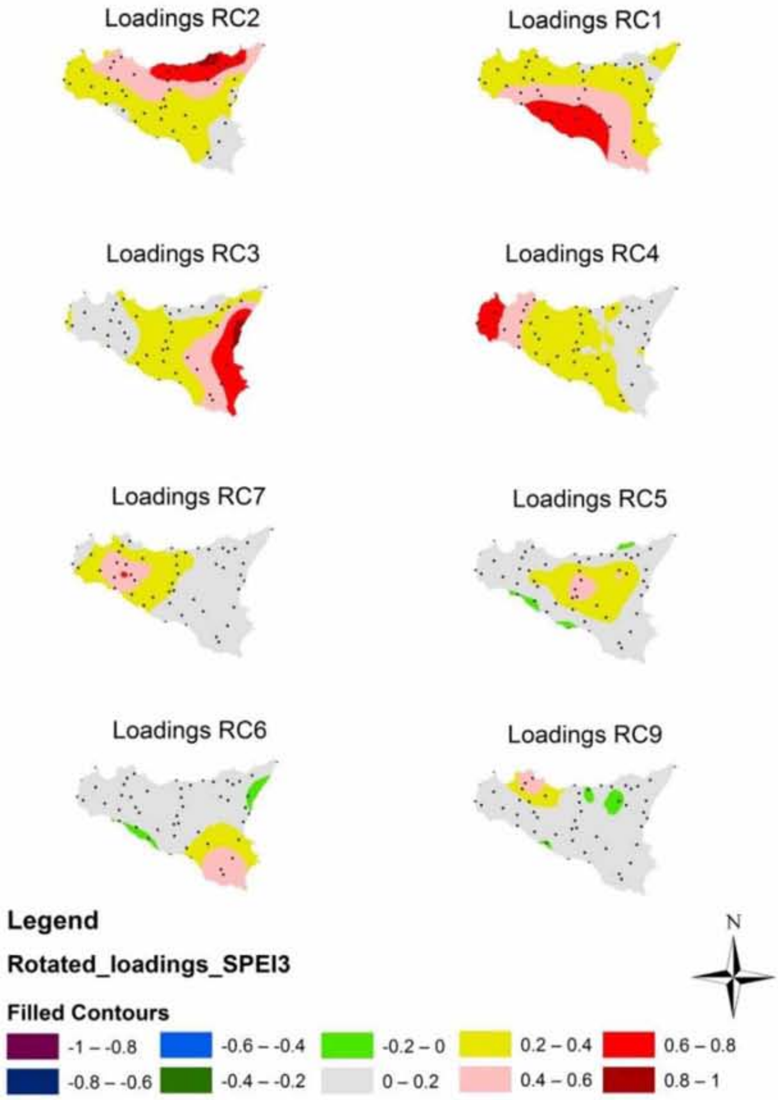

Figure II. 11 Loadings of first 8 rotated principal components for SPEI index of 3 months' time scale.

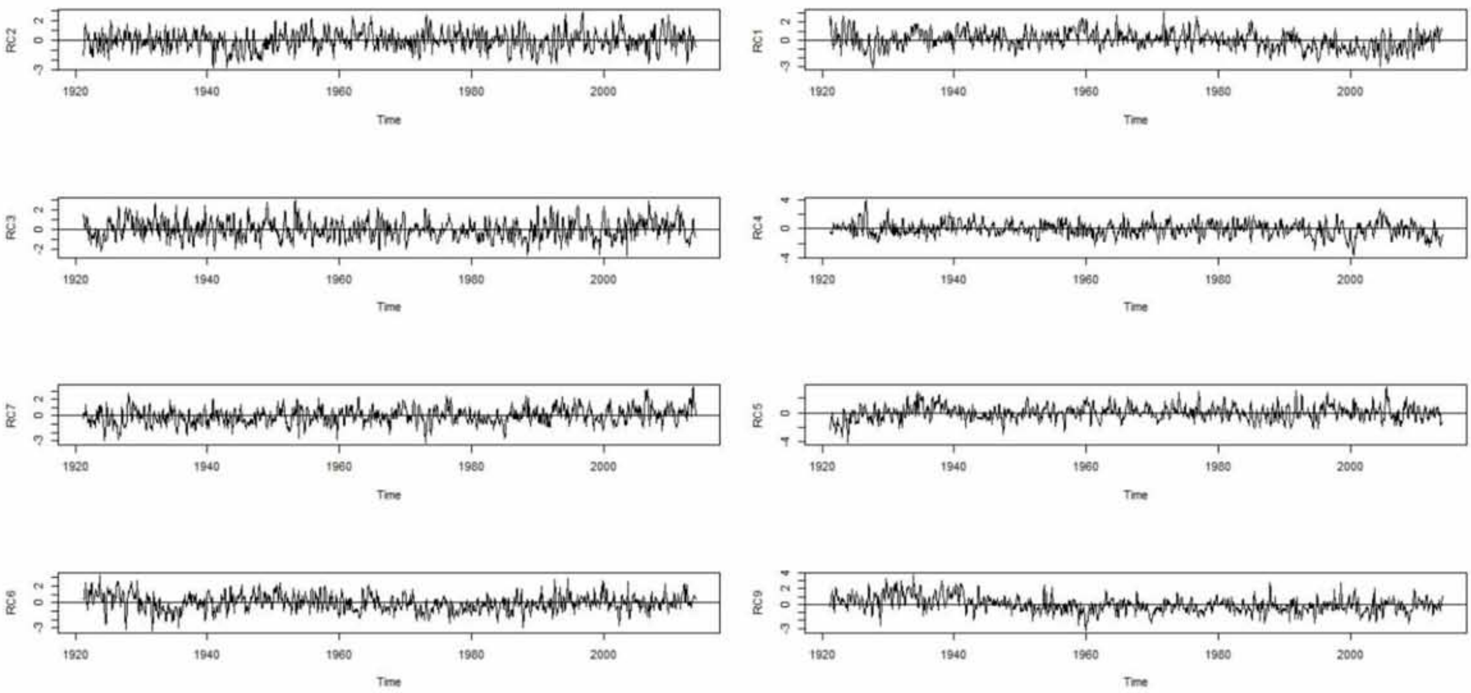

Figure II. 12 First 8 rotated scores for the period 1921-2013, based on SPEI index of 3 months' time scale.

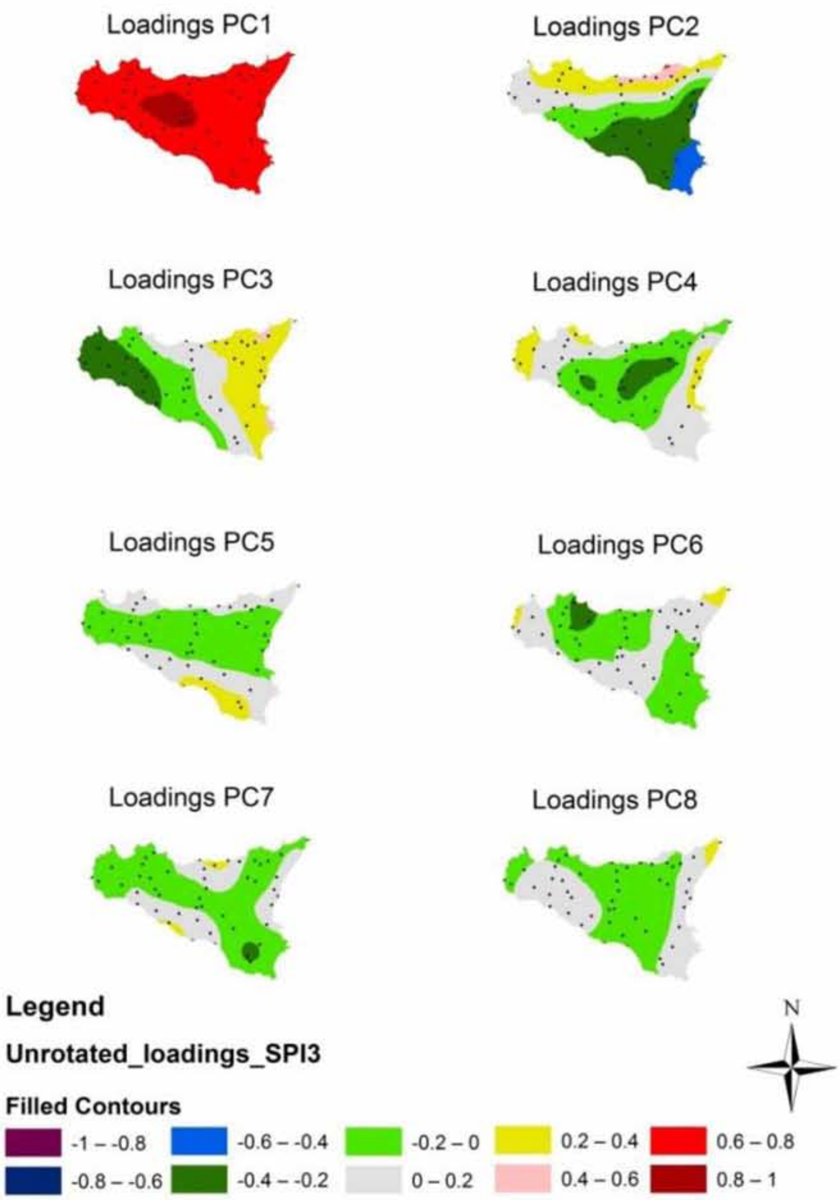

Figure II. 13 Loadings of first 8 unrotated principal components for SPI index of 3 months' time scale.

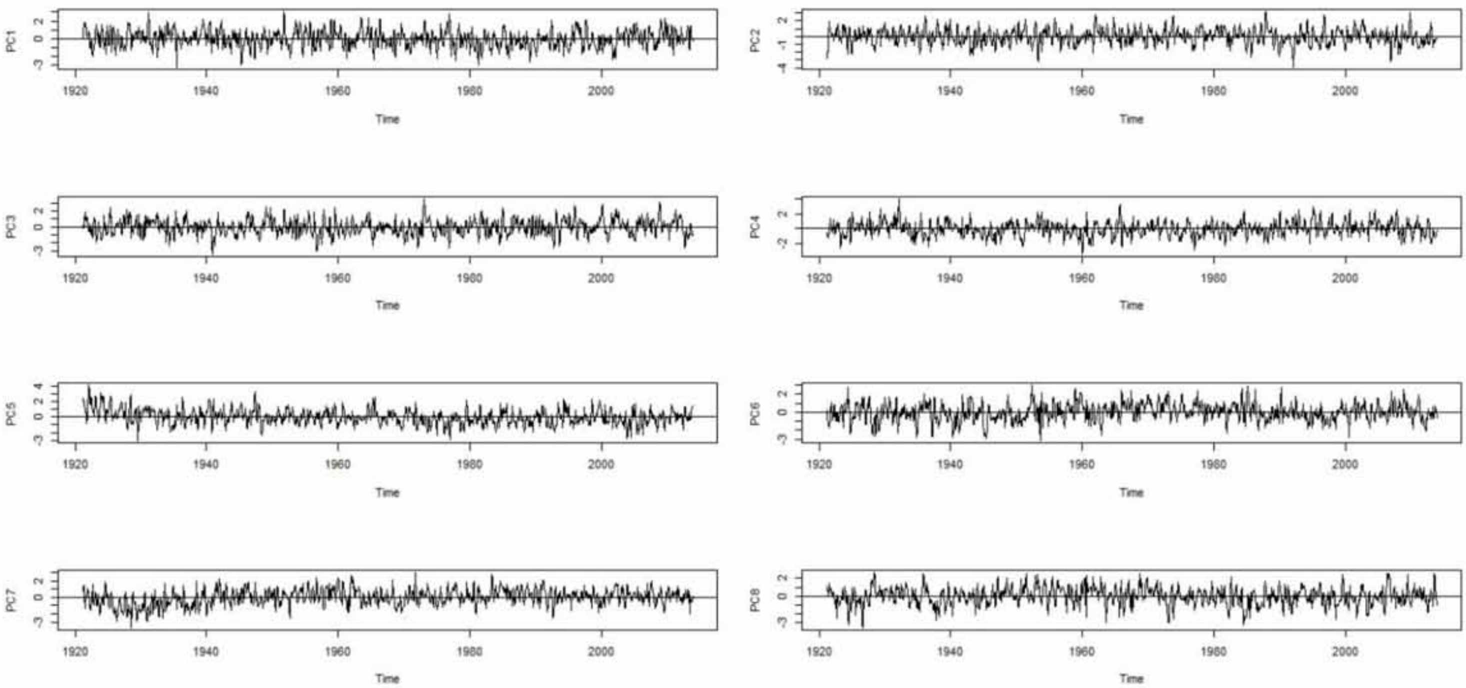

Figure II. 14 First 8 unrotated scores for the period 1921-2013, based on SPI index of 3 months' time scale.

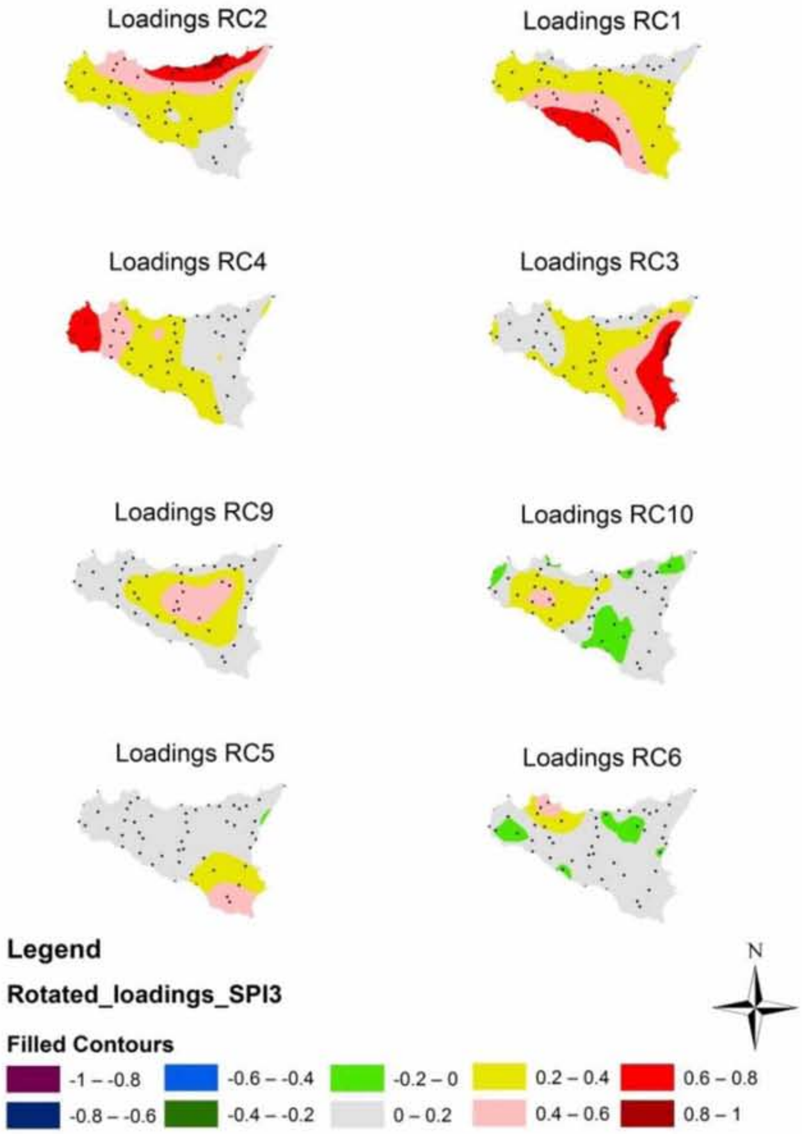

Figure II. 15 Loadings of first 8 rotated principal components for SPI index of 3 months' time scale.

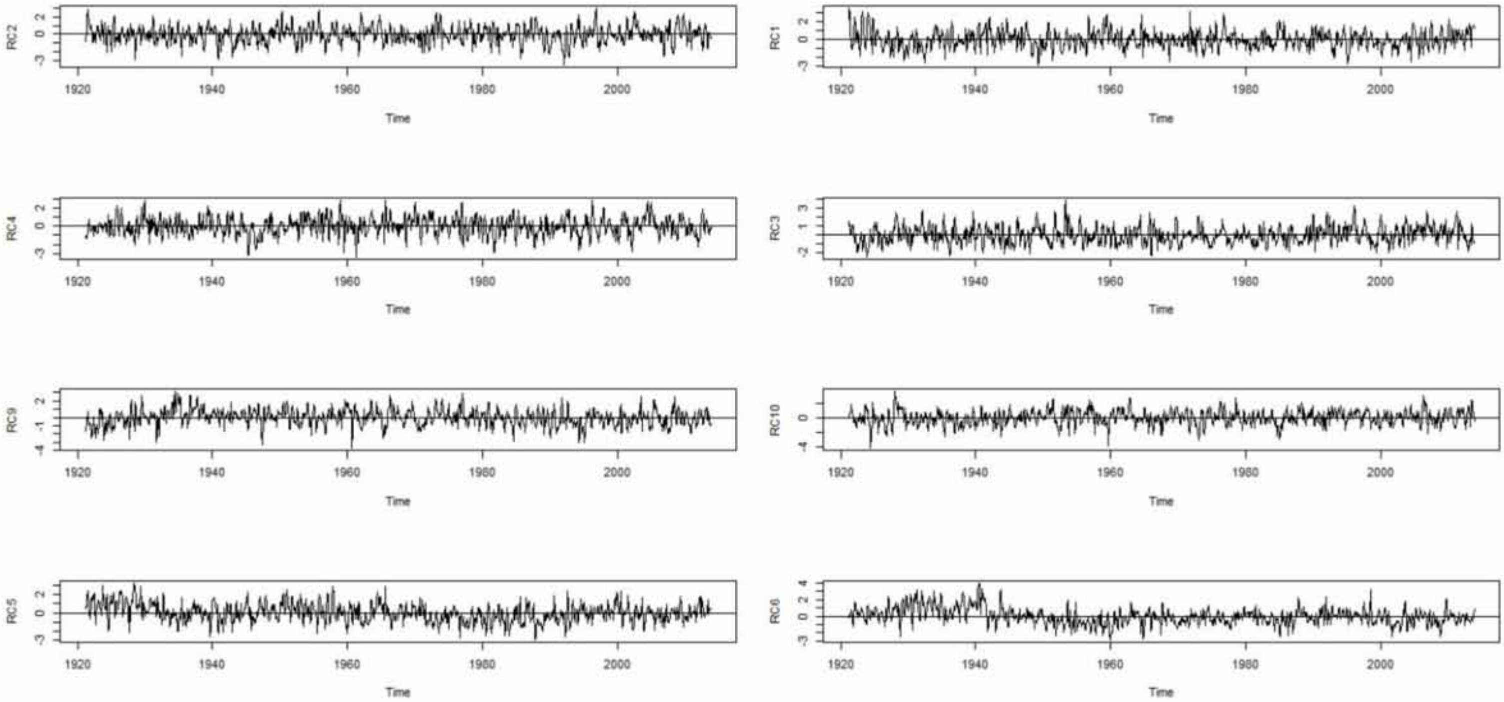

Figure II. 16 First 8 rotated scores for the period 1921-2013, based on SPI index of 3 months' time scale.

6 months' time scale:

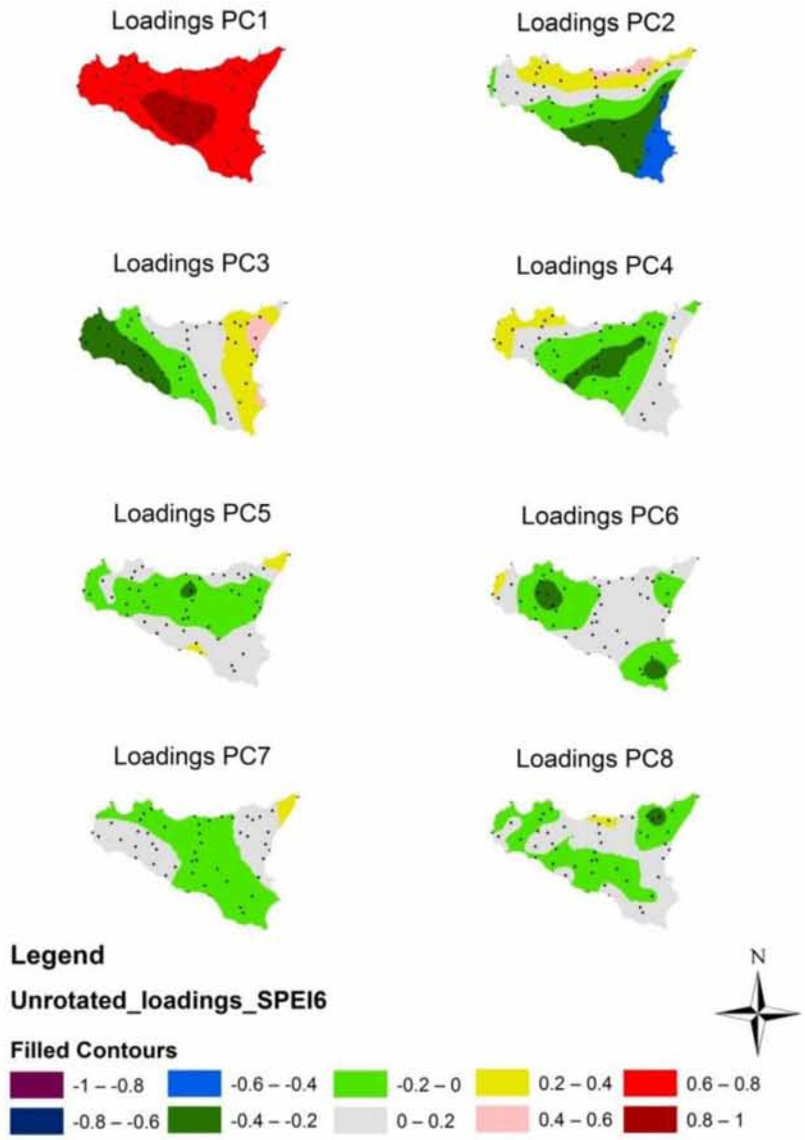

Figure II. 17 Loadings of first 8 unrotated principal components for SPEI index of 6 months' time scale.

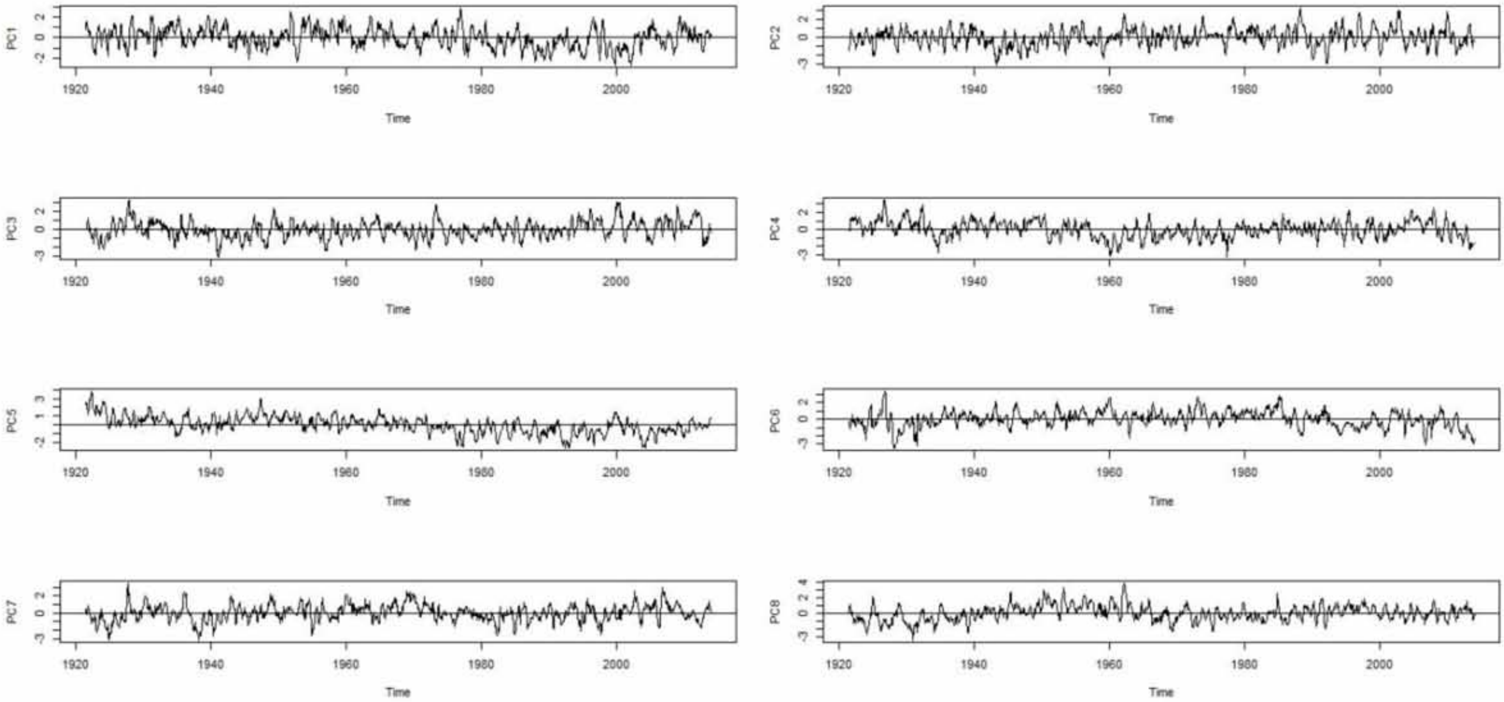

Figure II. 18 First 8 unrotated scores for the period 1921-2013, based on SPEI index of 6 months' time scale.

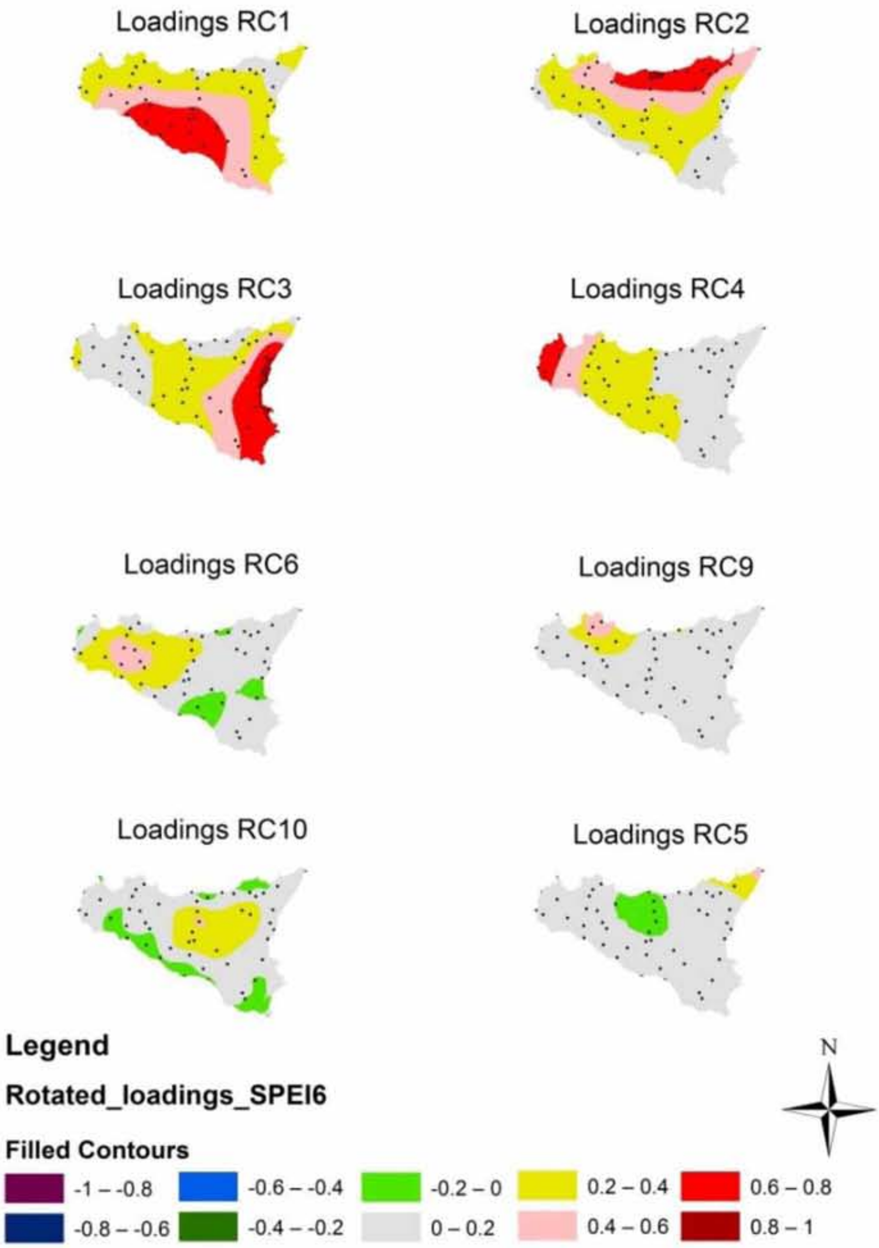

Figure II. 19 Loadings of first 8 rotated principal components for SPEI index of 6 months' time scale.

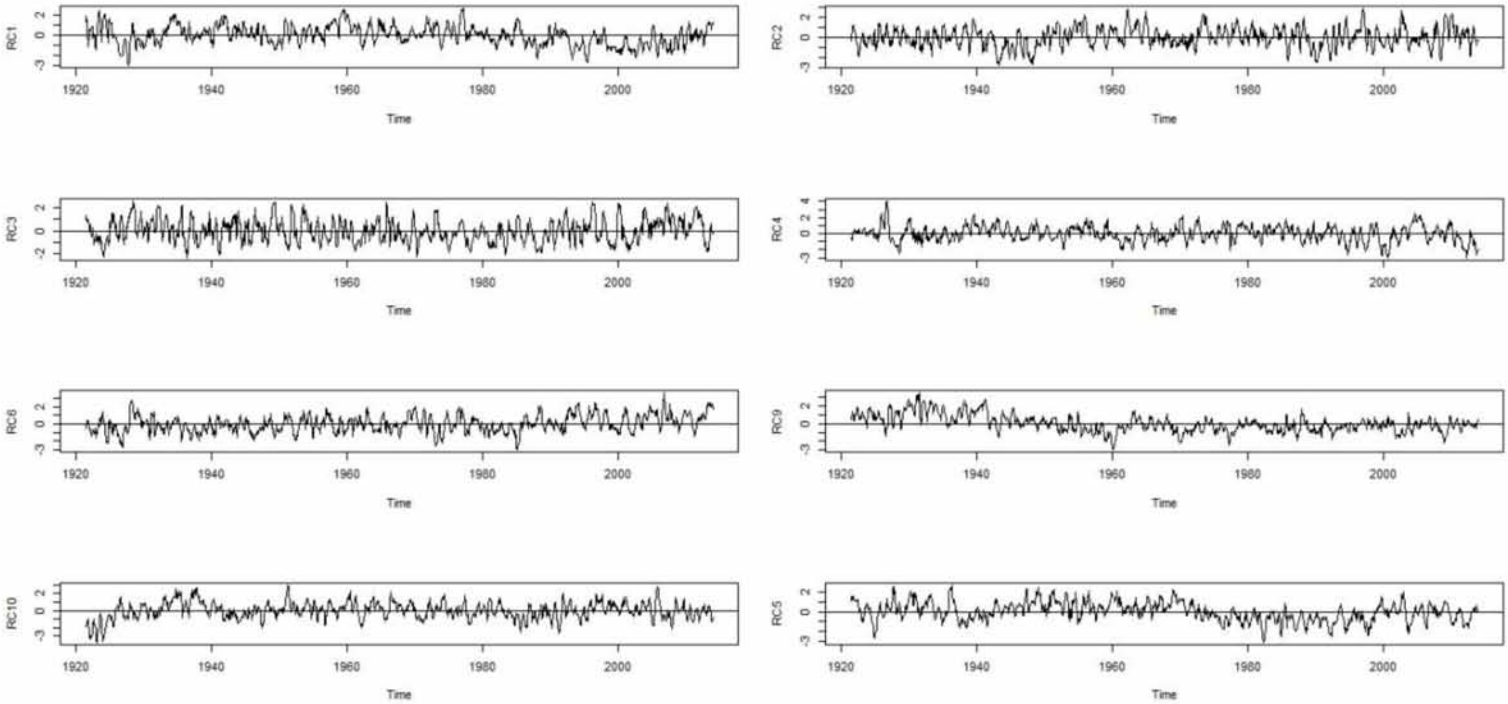

Figure II. 20 First 8 rotated scores for the period 1921-2013, based on SPEI index of 6 months' time scale.

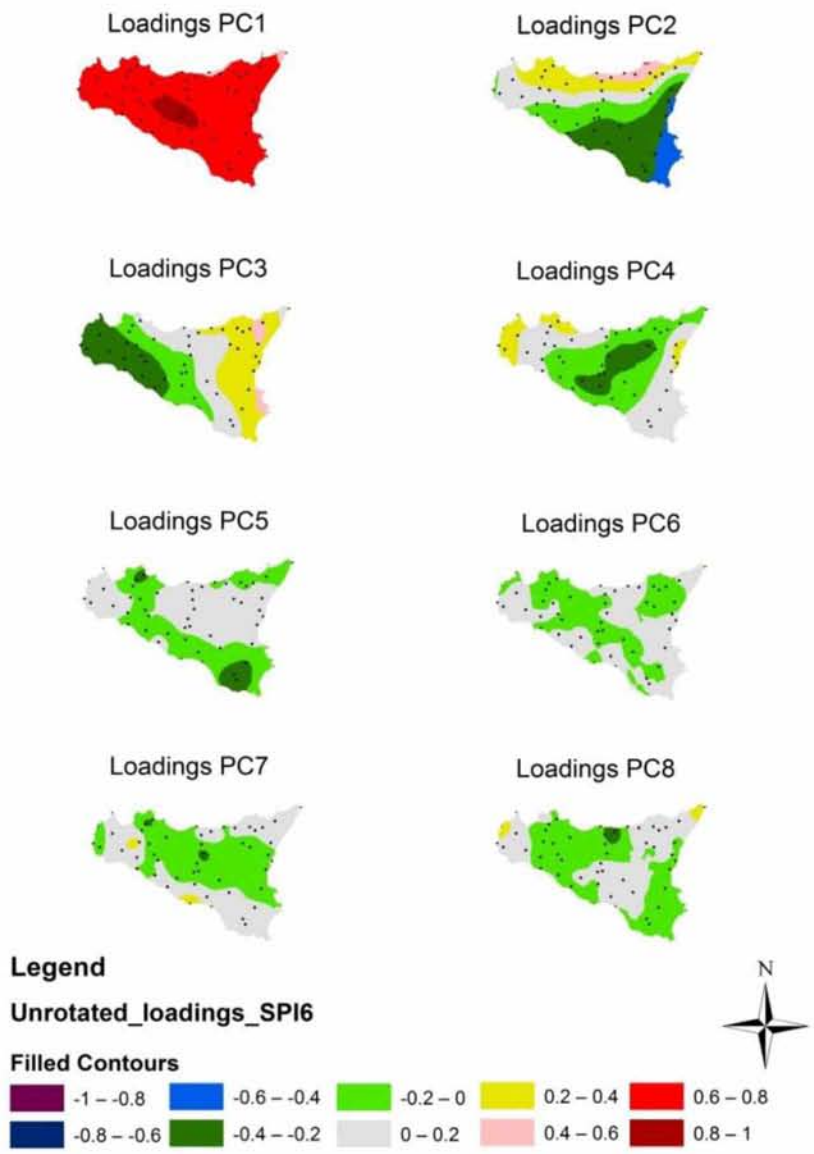

Figure II. 21 Loadings of first 8 unrotated principal components for SPI index of 6 months' time scale.

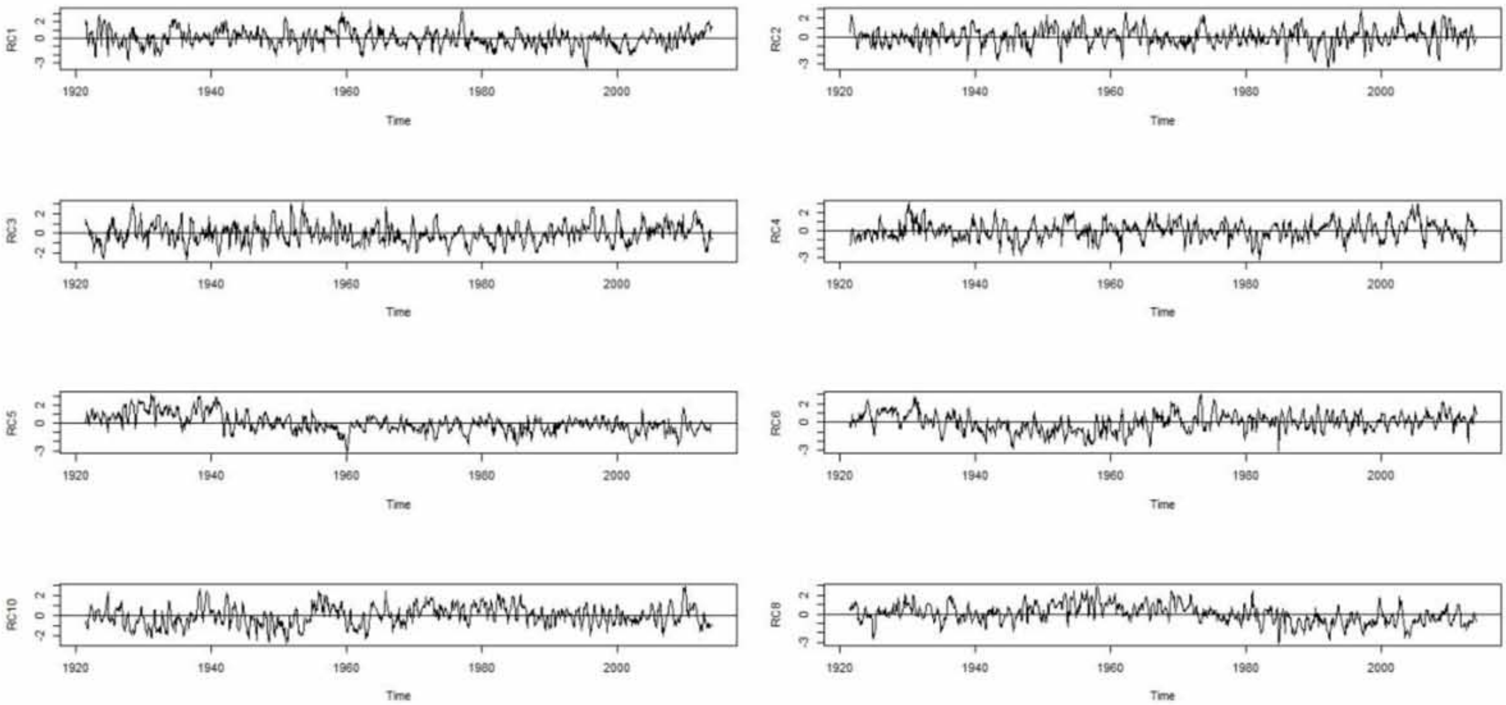

Figure II. 22 First 8 unrotated scores for the period 1921-2013, based on SPI index of 6 months' time scale.

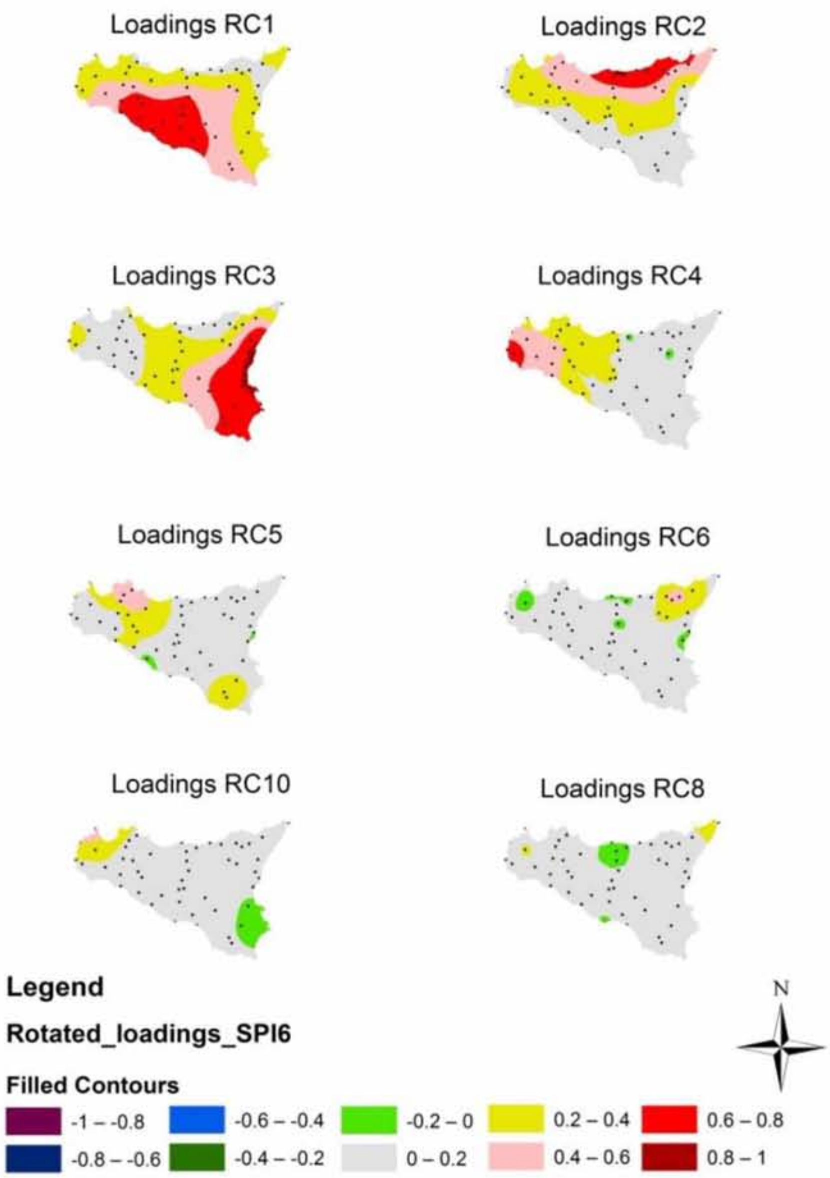

Figure II. 23 Loadings of first 8 rotated principal components for SPI index of 6 months' time scale.

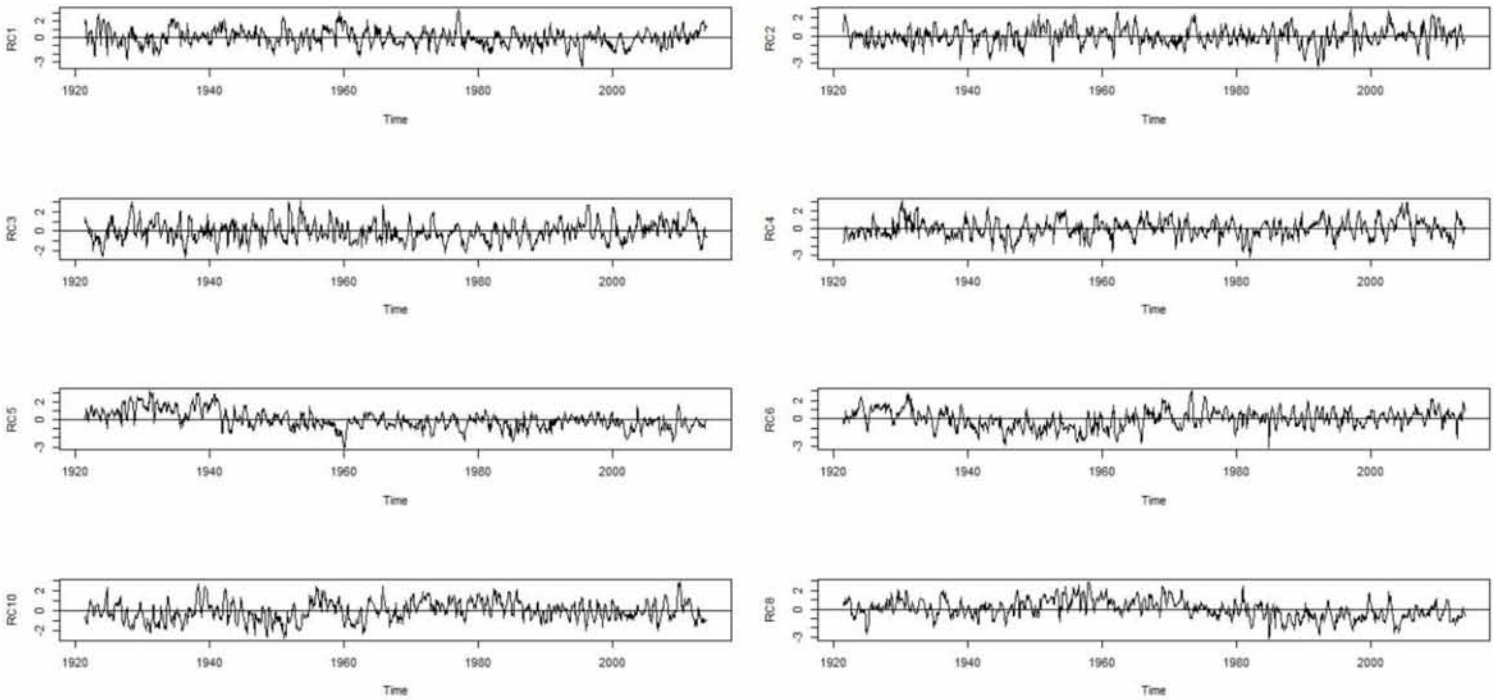

Figure II. 24 First 8 rotated scores for the period 1921-2013, based on SPI index of 6 months' time scale.

36 months' time scale:

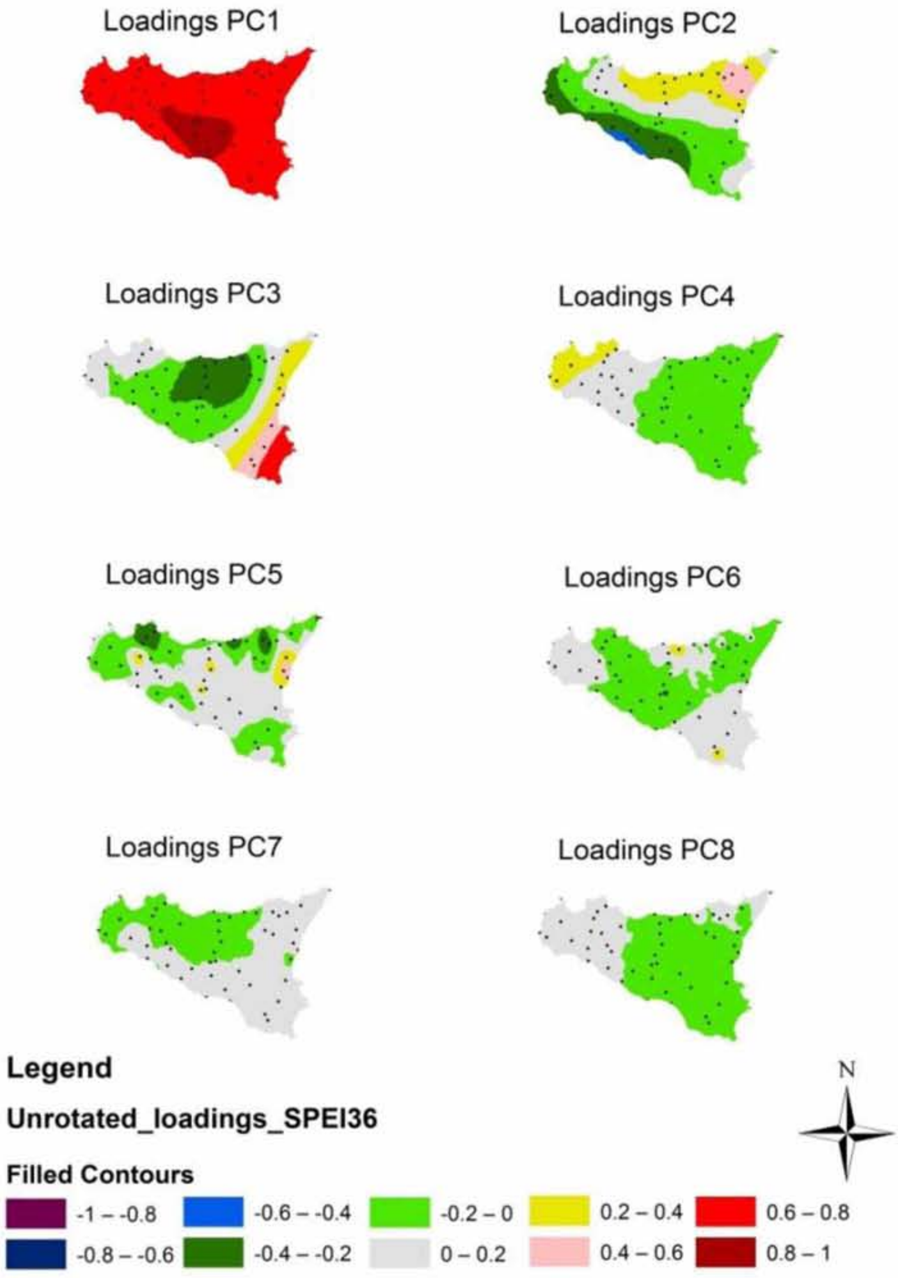

Figure II. 25 Loadings of first 8 unrotated principal components for SPEI index of 36 months' time scale.

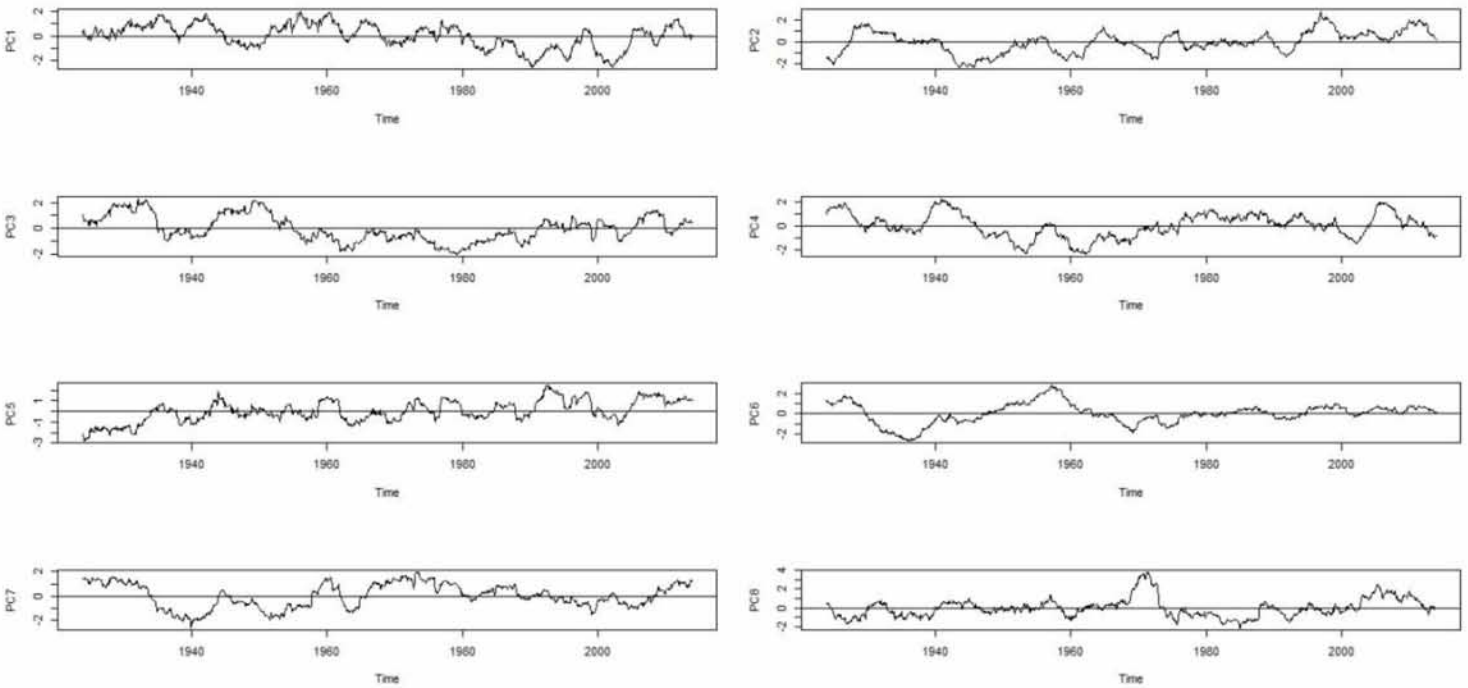

Figure II. 26 First 8 unrotated scores for the period 1921-2013, based on SPEI index of 36 months' time scale.

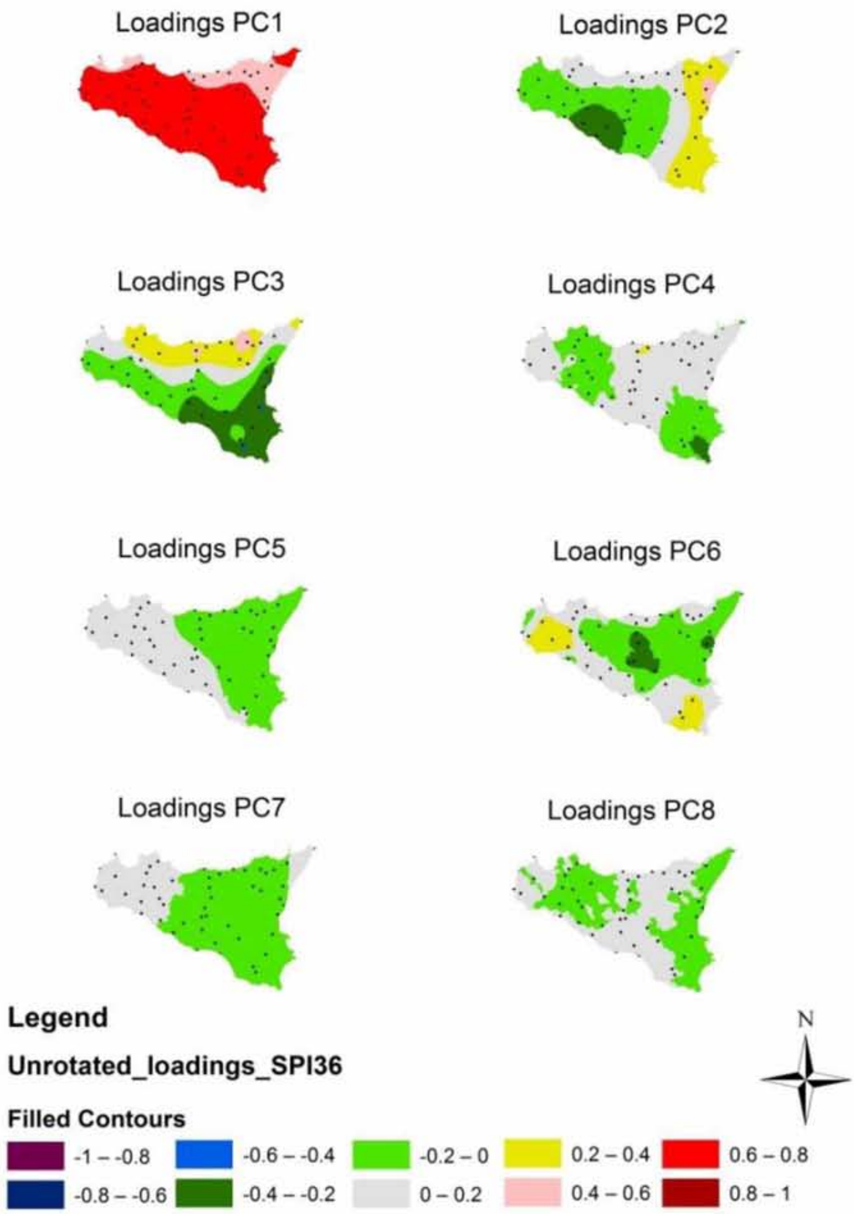

Figure II. 27 Loadings of first 8 unrotated principal components for SPI index of 36 months' time scale.

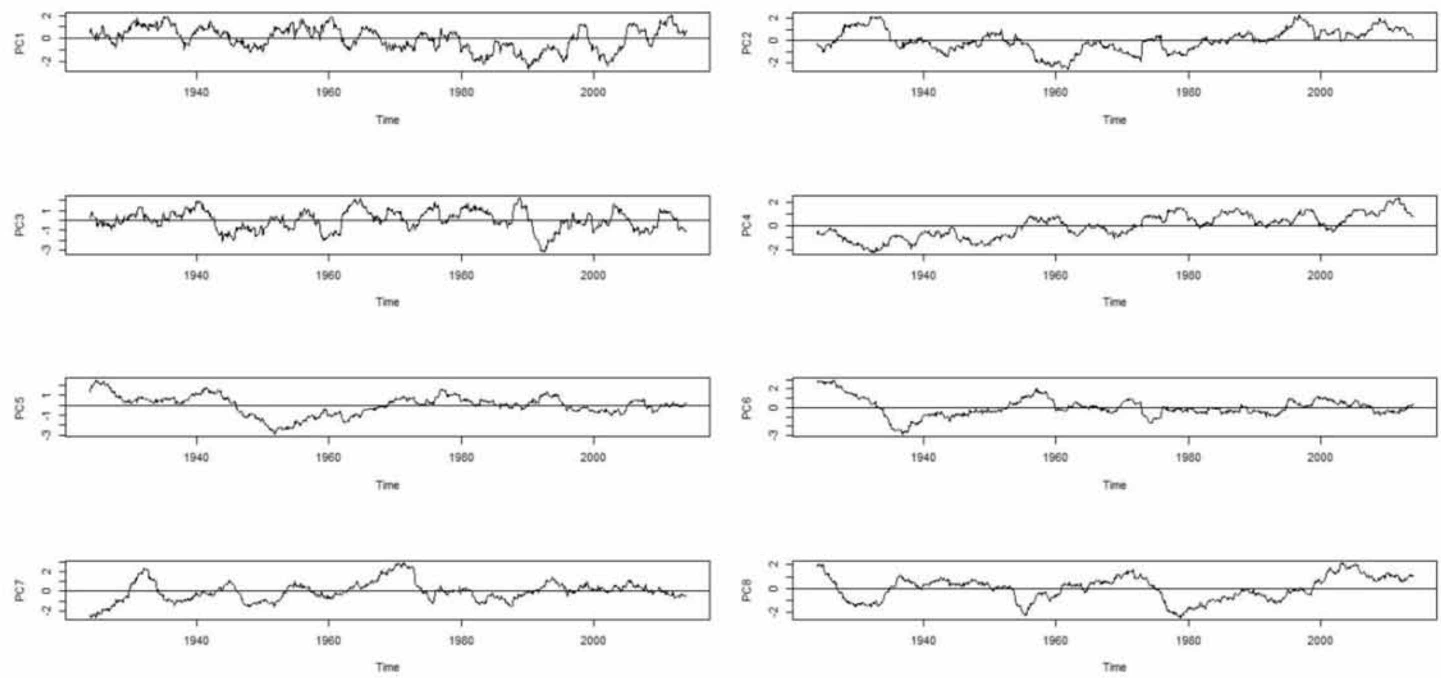

Figure II. 28 First 8 unrotated scores for the period 1921-2013, based on SPI index of 36 months' time scale.

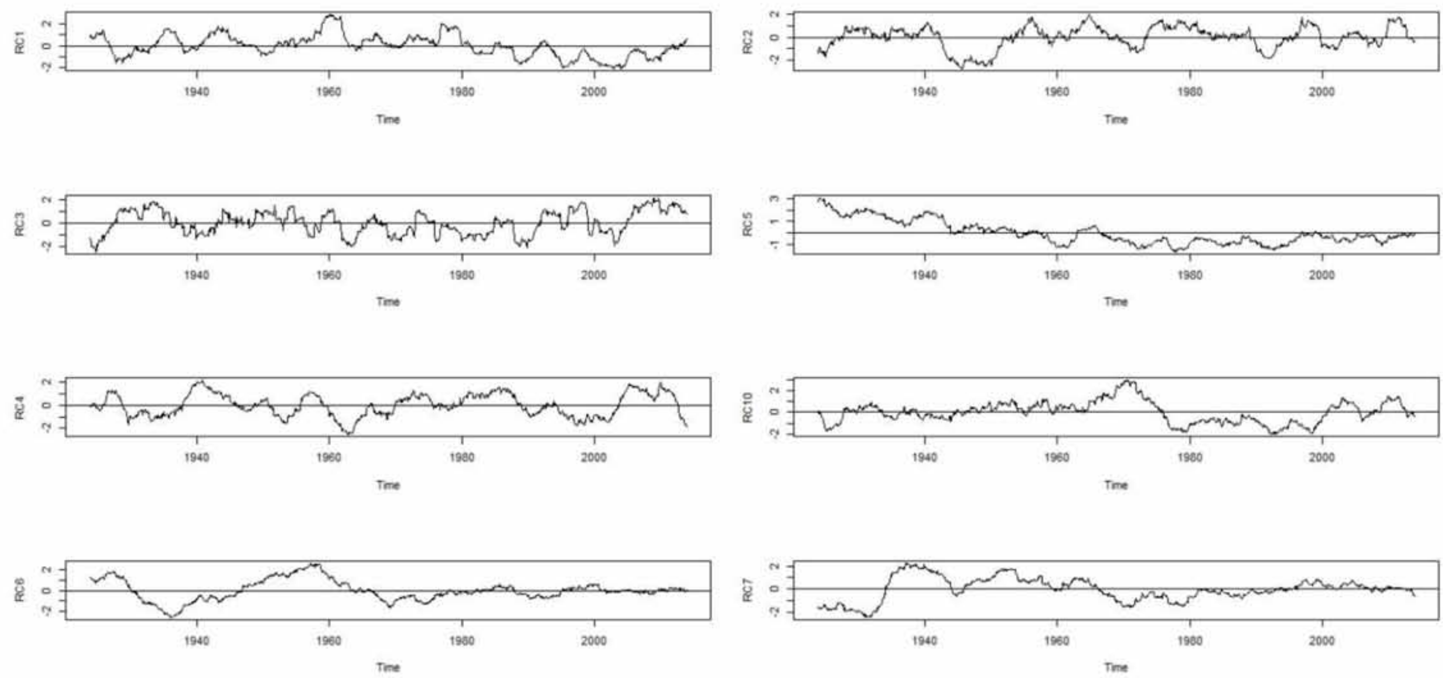

Figure II. 29 First 8 rotated scores for the period 1921-2013, based on SPEI index of 36 months' time scale.

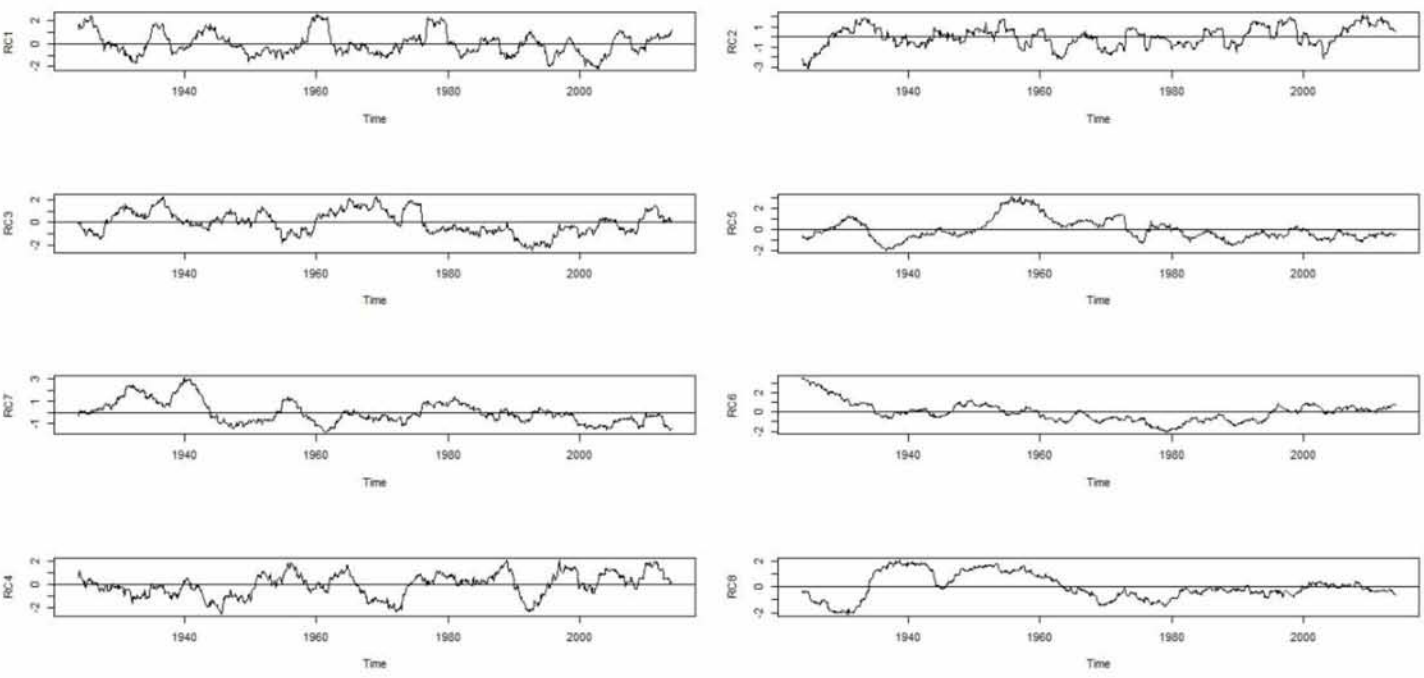

Figure II. 30 First 8 rotated scores for the period 1921-2013, based on SPI index of 36 months' time scale.