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Occurrence Probabilities of Wet and Dry Periods in Southern Italy through the SPI Evaluated on Synthetic Monthly Precipitation Series

Tommaso Caloiero [1], Beniamino Sirangelo [2], Roberto Coscarelli [3] and Ennio Ferrari [4,*]

[1] National Research Council—Institute for Agricultural and Forest Systems in Mediterranean (CNR-ISAFOM), Via Cavour 4/6, 87036 Rende, Italy; tommaso.caloiero@isafom.cnr.it
[2] Department of Environmental and Chemical Engineering (DIATIC), University of Calabria, Via P. Bucci 41C, 87036 Rende, Italy; beniamino.sirangelo@unical.it
[3] National Research Council—Research Institute for Geo-Hydrological Protection (CNR-IRPI), University of Calabria, Via Cavour 4/6, 87036 Rende, Italy; coscarelli@irpi.cnr.it
[4] Department of Computer Engineering, Modeling, University of Calabria, Electronics, and Systems Science (DIMES), Via P. Bucci 41C, 87036 Rende, Italy
* Correspondence: ennio.ferrari@unical.it; Tel.: +39-0984-496618

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Abstract: The present article investigates dry and wet periods in a large area of the Mediterranean basin. First, a stochastic model was applied to a homogeneous database of monthly precipitation values of 46 rain gauges in five regions of southern Italy. In particular, after estimating the model parameters, a set of 10^4 years of monthly precipitation for each rain gauge was generated by means of a Monte Carlo technique. Then, dry and wet periods were analyzed through the application of the standardized precipitation index (SPI) over 3-month and 6-month timespan (short-term) and 12-month and 24-month period (long-term). As a result of the SPI application on the generated monthly precipitation series, higher occurrence probabilities of dry conditions than wet conditions have been detected, especially when long-term precipitation scales are considered.

Keywords: monthly precipitation; stochastic model; SPI; dry and wet periods; southern Italy

1. Introduction

Recently, the adverse impacts of climate change have become a main focus of the scientific community, due to the possible intensification of extreme phenomena such as heat waves, forest fires, flood and droughts [1]. In fact, given the changes in the precipitation patterns triggered by anthropogenic climate change, several cities in the world are registering an increase in their vulnerability to flooding, also due to rapid urbanization [2,3]. Moreover, a warmer climate could cause an increase in the burned area and an extension of the fire season in the next decades [4]. In particular, the Mediterranean region has recently suffered from a temperature increase faster than the global mean and, with the warming and drying projections, this area could be affected by more frequent heat waves and dry spells [5]. In this scenario, the knowledge of drought phenomena plays an important role for an appropriate planning and management of water resources [6,7]. In fact, different drought events have affected Europe during recent decades [8–11] and an increase in the drought frequency is expected in this century in some seasons and areas [12,13], following the recently evidenced variability of precipitation and/or evapotranspiration [14–17]. The consequences of such changes can significantly affect some areas, such as the Mediterranean Basin, already under stress from a water shortage, due to a combination of a dry climate and excessive water demand [18]. At the same time, the knowledge of wet conditions is also paramount because extreme wet conditions can cause flooding, damage crops, reduce yields, and contribute to groundwater contamination [19–21]. In fact, climate change could also increase the risk of future hydrological extremes over a large regional scale and trigger further pressure on water resource availability [22]. For these reasons, recently, several studies have focused on the analyses of the distribution of dry and wet periods events in several parts of the world [23–29].

Generally, climate anomalies are evaluated by means of indices that allow scientists to characterize them in terms of intensity, duration, frequency, recurrence probability and spatial extent [30,31]. Among these indices, the Standardized Precipitation Index (SPI) [32,33] has found widespread application worldwide [34–38], in the Mediterranean basin [39–41] and also in Central [42] and Southern Italy [43–48].

The SPI can be evaluated for several time-scales and allows for the investigation of different dry or wet classes. Indeed, the SPI is considered one of the most robust and effective indices [49]. Moreover, in order to evaluate the SPI, only precipitation data are required, and so it is easier to calculate than more complex indices. Finally, the SPI allows for the comparison of dry or wet conditions in different areas and for different time periods [40,50].

Unfortunately, in the study of long dry and wet periods, two kinds of problems can affect the analysis. The first problem is related to the length of the precipitation series and to the limited number of drought events in the historical data, especially with a long duration [51]. The second problem is related to the presence of missing values in the precipitation series, which may significantly influence the estimate of the event duration and the character of their alternation [52]. In order to overcome such a difficulty, stochastic models are frequently used to produce long and complete precipitation series that are statistically similar to historical records [53]. Specifically, numerous approaches for the stochastic modeling of daily precipitation data are available in the hydrological and climatological literature [54–62]. However, very little work has been done on stochastic generation of monthly precipitation data [63] because in the past, low attention was paid to this time aggregation. In this context, several authors applied the Monte Carlo simulation for drought analysis [64]. In particular, Montaseri and Amirataee [65] evaluated the inherent performance of seven meteorological drought indices in several parts of the world characterized by different climatic conditions. They highlighted the advantages of application of the Monte Carlo technique in drought monitoring and recommended to not only count on historical data series when long-term drought events have to be generalized. In this paper, as opposed to past studies which have focused on the analysis of daily precipitation in limited area, a recently proposed model [48] for the stochastic simulation of monthly precipitation data has been adapted and applied on a large area. The aim of this study is to analyze the probabilistic occurrence of dry and wet periods through the application of the SPI to monthly precipitation series generated by a Monte Carlo procedure based on a data set of 46 rain gauges uniformly distributed on a large part of Southern Italy.

The paper has been structured in two main sections. In Section 2, first a brief description of the study area is presented and, then, the procedure for stochastic modeling of precipitation at monthly scale and the SPI method have been described. In Section 3, results of the application of the SPI on the monthly precipitation, generated for each rain gauge by means of a Monte Carlo technique based on the stochastic model, are presented and discussed.

2. Materials and Methods

2.1. Case Study

The region under investigation, with an area of about 85,000 km^2, is a large portion of southern Italy, ranging from Campania and Apulia in the North, to Sicily in the South (Figure 1).

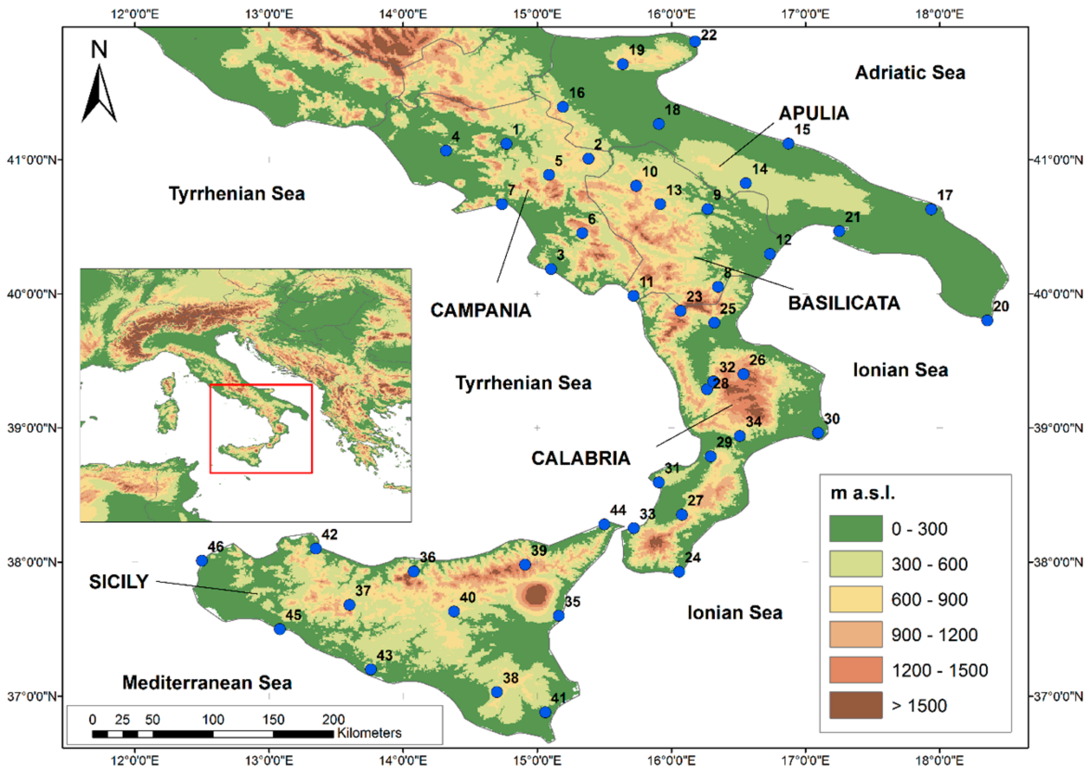

Figure 1. Study area with the locations of the 46 rain gauges.

The study area is located in the middle of the Mediterranean basin and is characterized by peculiar climatic conditions. In particular, the islands and the coastal areas are dominated by a Mediterranean climatic regime, characterized by mild and rainy winters and hot and dry summers. In the inland and the mountainous areas an Apennine climate prevails, with very cold winters and hot summers, and a rather uniform precipitation distribution throughout the year.

The database used in this study has been extracted by the one presented in Longobardi et al. [66] in which available precipitation data were tested for time series homogeneity through the combined use of direct and indirect methods. The database consists of 46 monthly precipitation series, in the period 1916–2006, with an average density of about 1 station per 1850 km^2 (Figure 1 and Table 1).

2.2. Stochastic Modeling of Monthly Precipitation

In this subsection, the procedure proposed by Caloiero et al. [48] for the generation of synthetic monthly precipitation data is briefly presented.

Being H_{ij} (j = month; i = year) the sequence of random variables which describes the cumulated precipitation from a non-specified origin i = 0, and defining N_j as the number of days of the j-month and I_0 as a generic reference value of the daily precipitation intensity (assumed in this work equal to 1 mm/day), the dimensionless random variables:

$$X_{ij} = \frac{H_{ij}}{N_j I_0}, \tag{1}$$

indicate a sequence which can be described as a discrete cyclostationary stochastic process with period P equal to 12 months.

By adopting the transformation $Y_{ij} = X_{ij}^{\lambda}$ (for $\lambda > 0$ and $X_{ij} > 0$), finalized to the gaussianisation of the process, the sequence of random variables Z_k:

$$Z_k = \frac{Y_{ij} - \mu_{Y,j}}{\sigma_{Y,j}} \text{ with } k = 12i + j, \quad (2)$$

is a standardized stationary Gaussian stochastic process, where both the functions $\mu_{Y,j} = E_i(Y_{ij})$ and $\sigma_{Y,j} = \sqrt{E_i\left(Y_{ij}^2\right) - \mu_{Y,j}^2}$ are employed to the deseasonalization of the monthly precipitation process.

Table 1. Main details of the selected rain gauges.

ID Code	Rain Gauge	Region	Longitude	Latitude	No. of Years of Observation
1	Benevento (Genio Civile)	Campania	14.769	41.117	72
2	Bisaccia	Campania	15.380	41.008	82
3	Casalvelino	Campania	15.102	40.184	76
4	Caserta (Genio Civile)	Campania	14.319	41.067	81
5	Nusco	Campania	15.088	40.886	84
6	S. Angelo a Fasanella	Campania	15.336	40.451	80
7	Salerno (Genio Civile)	Campania	14.736	40.667	79
8	Cersosimo	Basilicata	16.348	40.051	65
9	Grassano	Basilicata	16.270	40.632	61
10	Lagopesole	Basilicata	15.737	40.804	83
11	Maratea	Basilicata	15.717	39.984	62
12	Pisticci	Basilicata	16.735	40.295	67
13	Vaglio di Lucania	Basilicata	15.916	40.667	68
14	Altamura	Apulia	16.554	40.824	86
15	Bari (Osservatorio)	Apulia	16.873	41.118	86
16	Biccari	Apulia	15.191	41.393	84
17	Brindisi	Apulia	17.938	40.629	86
18	Cerignola	Apulia	15.906	41.264	85
19	San Marco in Lamis	Apulia	15.637	41.711	87
20	Santa Maria di Leuca	Apulia	18.356	39.800	85
21	Taranto	Apulia	17.251	40.465	86
22	Vieste	Apulia	16.176	41.881	86
23	Campotenese	Calabria	16.068	39.873	79
24	Capo Spartivento	Calabria	16.056	37.927	68
25	Cassano allo Ionio	Calabria	16.319	39.783	74
26	Cecita	Calabria	16.538	39.400	70
27	Cittanova	Calabria	16.078	38.352	77
28	Cosenza	Calabria	16.265	39.287	79
29	Filadelfia	Calabria	16.293	38.787	76
30	Isola di Capo Rizzuto	Calabria	17.094	38.961	67
31	Joppolo	Calabria	15.905	38.592	68
32	San Pietro in Guarano	Calabria	16.314	39.346	72
33	Scilla	Calabria	15.720	38.252	64
34	Tiriolo	Calabria	16.510	38.940	58
35	Acireale	Sicily	15.159	37.599	85
36	Castelbuono	Sicily	14.079	37.929	81
37	Castronuovo di Sicilia	Sicily	13.599	37.679	82
38	Chiaramonte Gulfi	Sicily	14.699	37.029	86
39	Floresta	Sicily	14.909	37.979	85
40	Leonforte	Sicily	14.379	37.629	81
41	Noto	Sicily	15.059	36.879	82
42	Palermo Oss. Astronomico	Sicily	13.349	38.099	61
43	Palma di Montechiaro	Sicily	13.759	37.199	81
44	San Saba	Sicily	15.499	38.279	69
45	Sciacca	Sicily	13.079	37.499	85
46	Trapani	Sicily	12.499	38.009	84

The mean $\mu_{Y,j}$ and the variance $\sigma_{Y,j}^2$ functions can be described by means of expansion of truncated Fourier series, expressed as linear superposition of sine and cosine functions with different frequencies.

The estimation procedures of the number of harmonics ($N_h^{(\mu)}$ and $N_h^{(\sigma^2)}$) and of the parameters of both the functions $\mu_{Y,j}$ and $\sigma_{Y,j}$ are well described in Caloiero et al. [48].

Generally, a weak correlative structure appears in the sequence of the random variables Z_k. If this correlation is significant, it can be modelled as an autoregressive process of order p. Being Z_k standardized Gaussian variables and considering a white noise standardized Gaussian process W_k, it can be written:

$$Z_k = \psi_0 W_k + \sum_{l=1}^{p} \varphi_l Z_{k-l}, \tag{3}$$

Using the sample values $r_{Z,l}$ of the autocorrelation coefficients of lag l (l = 1, .., p) of the sequence Z_k, by solving the Yule-Walker system it is possible to estimate the parameters φ_l and consequently ψ_0 with the following relation [67]:

$$\hat{\psi}_0 = \sqrt{1 - \textstyle\sum_{l=1}^{p} \hat{\varphi}_l r_{Z,l}} \tag{4}$$

The p-order of the autoregressive process can be fixed as the minimum value for which cannot be rejected the hypothesis $H_{0,p}^{(\rho_v)}$ that the sample biases $w_{p,k} = \left(z_k - \sum_{l=1}^{p} \hat{\varphi}_l z_{k-l}\right)/\hat{\psi}_0$ with $k = p + 1$, $p + 2$ are uncorrelated (for lag v = 1, 2, …). The Anderson test [68,69] allows to test the hypothesis $H_{0,p}^{(\rho_v)}$ at a significance level α. The test must be applied also in the case p = 0, for which $W_{0,k} = Z_k$ and $w_{0,k} = z_k$, in order to verify the hypothesis that the process Z_k can be considered as a white noise.

2.3. Standardized Precipitation Index

In this study, dry and wet periods were expressed using the SPI [32] on different time scales. Indeed, it is generally agreed that the SPI on short-term scales (e.g., 3 or 6 months) describes drought affecting vegetation and agricultural practices, while on long-term scales (e.g., 12 or 24 months) it is a broad proxy for water resource management [70]. Angelidis et al. [71] described in detail the calculation of SPI. The index is computed by fitting an appropriate probability density function (pdf) to the frequency distribution of precipitation summed over the time scale of interest (usually 3, 6, 12, and 24 months). This is performed separately for each time scale and for each location in space. Computation of the SPI involves fitting a gamma function to a given time series of precipitation, with probability density function (pdf) defined as:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \text{ for } x > 0, \tag{5}$$

where $\alpha > 0$ is a shape parameter, $\beta > 0$ is a scale parameter, $x > 0$ is the amount of precipitation and $\Gamma(\alpha)$ is the gamma function. Fitting the distribution to the data requires α and β to be estimated for each month of the year and for each time aggregation. Using the approximation of Thom [72], these parameters can be estimated as follows:

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right), \beta = \frac{\overline{x}}{\alpha} \text{ with } A = \ln(\overline{x}) - \frac{\sum \ln(x)}{n}, \tag{6}$$

where n is the number of observations. Integrating the pdf with respect to x yields the cumulative distribution function (cdf) $G(x)$:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \int_0^x x^{\alpha-1} e^{-x/\beta} dx, \tag{7}$$

It is possible to have several zero values in a sample set. In order to account for zero value probability, since the gamma distribution is undefined for $x = 0$, the cdf for the gamma distribution is modified as:

$$H(x) = q + (1 - q)\, G(x), \tag{8}$$

where q is the probability of zero precipitation, given by the ratio between the number of zeros in the precipitation series (m) and the number of observations (n).

Finally, the cdf is transformed into the standard normal distribution to yield the SPI. Following the approximate conversion provided by Abramowitz and Stegun [73], it results:

$$z = \mathrm{SPI} = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \text{ for } 0 < H(x) < 0.5, \tag{9}$$

$$z = \mathrm{SPI} = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), t = \sqrt{\ln\left(\frac{1}{(1 - H(x))^2}\right)} \text{ for } 0.5 < H(x) < 1, \tag{10}$$

where c_0, c_1, c_2, d_1, d_2 and d_3 are mathematical constants.

Although McKee et al. [32] originally proposed a classification restricted only to drought periods, it has become customary to use the index to classify wet periods as well. Table 2 reports the climatic classification according to the SPI, provided by the National Drought Mitigation Center (NDMC, http://drought.unl.edu).

Table 2. Climate classification according to the Standardized Precipitation Index (SPI) values [32].

SPI Value	Class	Probability (%)
SPI $\geq$ 2.0	Extremely wet	2.3
1.5 $\leq$ SPI < 2.0	Severely wet	4.4
1.0 $\leq$ SPI < 1.5	Moderately wet	9.2
0.0 $\leq$ SPI < 1.0	Mildly wet	34.1
$-1.0 \leq$ SPI < 0.0	Mild drought	34.1
$-1.5 \leq$ SPI < -1.0	Moderate drought	9.2
$-2.0 \leq$ SPI < -1.5	Severe drought	4.4
SPI < -2.0	Extreme drought	2.3

3. Results

In order to generate the long synthetic monthly precipitation series, for each of the selected 46 rain gauges, the parameters of the applied model (λ, number of harmonics $N_h^{(\mu)}$ and $N_h^{(\sigma^2)}$, and p order of the autoregressive model) were estimated (Table 3). In particular, for the mean function, the number of harmonics $N_h^{(\mu)}$ have been evaluated equal to 2 for almost all the rain gauges, with the exception of the Capo Spartivento, Castelbuono, Floresta, Palermo and Trapani gauges for which 3 harmonics are needed. From Figure 1 it can be easily seen that all these 5 rain gauges lies on an ideal horizontal line, thus evidencing a possible connection between the obtained results and the latitude. Moreover, 4 out 5 of these rain gauges, all in the northern side of Sicily, are exposed to the north-western air currents. For the variance function, Table 3 shows more heterogeneous results in the number of harmonics $N_h^{(\sigma^2)}$: 1 harmonic has been evaluated for 15 out of 46 rain gauges (33%), 2 harmonics for 25 rain gauges (54%) and 3 harmonics for the other 6 rain gauges (13%), thus no clear clusters can be identified.

For all the rain gauges, the sequences of observed values z_k showed low linear correlation coefficients, but not low enough to consider the process Z_k uncorrelated. In fact, the application of the Anderson test, with a lag $v_{max} = 24$, to the z_k series evidenced that only for 18 rain gauges the process Z_k can be considered as a white noise ($p = 0$), while for the other 28 precipitation series, it is sufficient to adopt an autoregressive model of order $p = 1$.

Table 3. Values of the transformation parameter λ, number of harmonics $N_h^{(\mu)}$ and $N_h^{(\sigma^2)}$ for the mean and the variance functions, respectively, and p-order of the autoregressive model, estimated for each rain gauge.

ID Code	Rain Gauge	λ	$N_h^{(\mu)}$	$N_h^{(\sigma^2)}$	p
1	Benevento (Genio Civile)	0.436	2	1	1
2	Bisaccia	0.546	2	1	1
3	Casalvelino	0.490	2	3	0
4	Caserta (Genio Civile)	0.473	2	2	1
5	Nusco	0.510	2	2	1
6	S.Angelo a Fasanella	0.429	2	2	1
7	Salerno (Genio Civile)	0.433	2	2	0
8	Cersosimo	0.359	2	1	0
9	Grassano	0.429	2	2	1
10	Lagopesole	0.469	2	2	1
11	Maratea	0.461	2	2	0
12	Pisticci	0.352	2	1	1
13	Vaglio Di Lucania	0.444	2	3	0
14	Altamura	0.431	2	2	0
15	Bari (Osservatorio)	0.413	2	2	0
16	Biccari	0.488	2	2	1
17	Brindisi	0.393	2	2	0
18	Cerignola	0.407	2	1	1
19	San Marco in Lamis	0.431	2	2	0
20	Santa Maria di Leuca	0.383	2	3	1
21	Taranto	0.374	2	2	1
22	Vieste	0.392	2	1	1
23	Campotenese	0.466	2	2	1
24	Capo Spartivento	0.338	3	2	0
25	Cassano allo Ionio	0.473	2	2	0
26	Cecita	0.442	2	2	1
27	Cittanova	0.401	2	1	1
28	Cosenza	0.477	2	2	1
29	Filadelfia	0.477	2	3	1
30	Isola di Capo Rizzuto	0.315	2	3	1
31	Joppolo	0.498	2	1	0
32	San Pietro in Guarano	0.513	2	2	1
33	Scilla	0.484	2	1	1
34	Tiriolo	0.405	2	2	1
35	Acireale	0.299	2	1	0
36	Castelbuono	0.390	3	2	0
37	Castronuovo Di Sicilia	0.389	2	1	0
38	Chiaramonte Gulfi	0.371	2	1	1
39	Floresta	0.378	3	2	0
40	Leonforte	0.363	2	1	1
41	Noto	0.320	2	1	1
42	Palermo Oss. Astronomico	0.431	3	2	0
43	Palma di Montechiaro	0.333	2	3	0
44	San Saba	0.381	2	2	1
45	Sciacca	0.331	2	1	1
46	Trapani	0.408	3	2	1

After the parameters estimation, 10^4 years long synthetic series have been generated for each rain gauge through a Monte Carlo procedure, and the SPI data were evaluated both for short (SPI3 and SPI6) and long (SPI12 and SPI24) time scales. Considering the SPI classification (Table 2), the occurrence probabilities of the various classes of dry and wet conditions were evaluated for each rain gauge. The results were also spatially interpolated using a spline technique.

Figure 2 shows the results obtained through the evaluation of the SPI over a 3-month timespan.

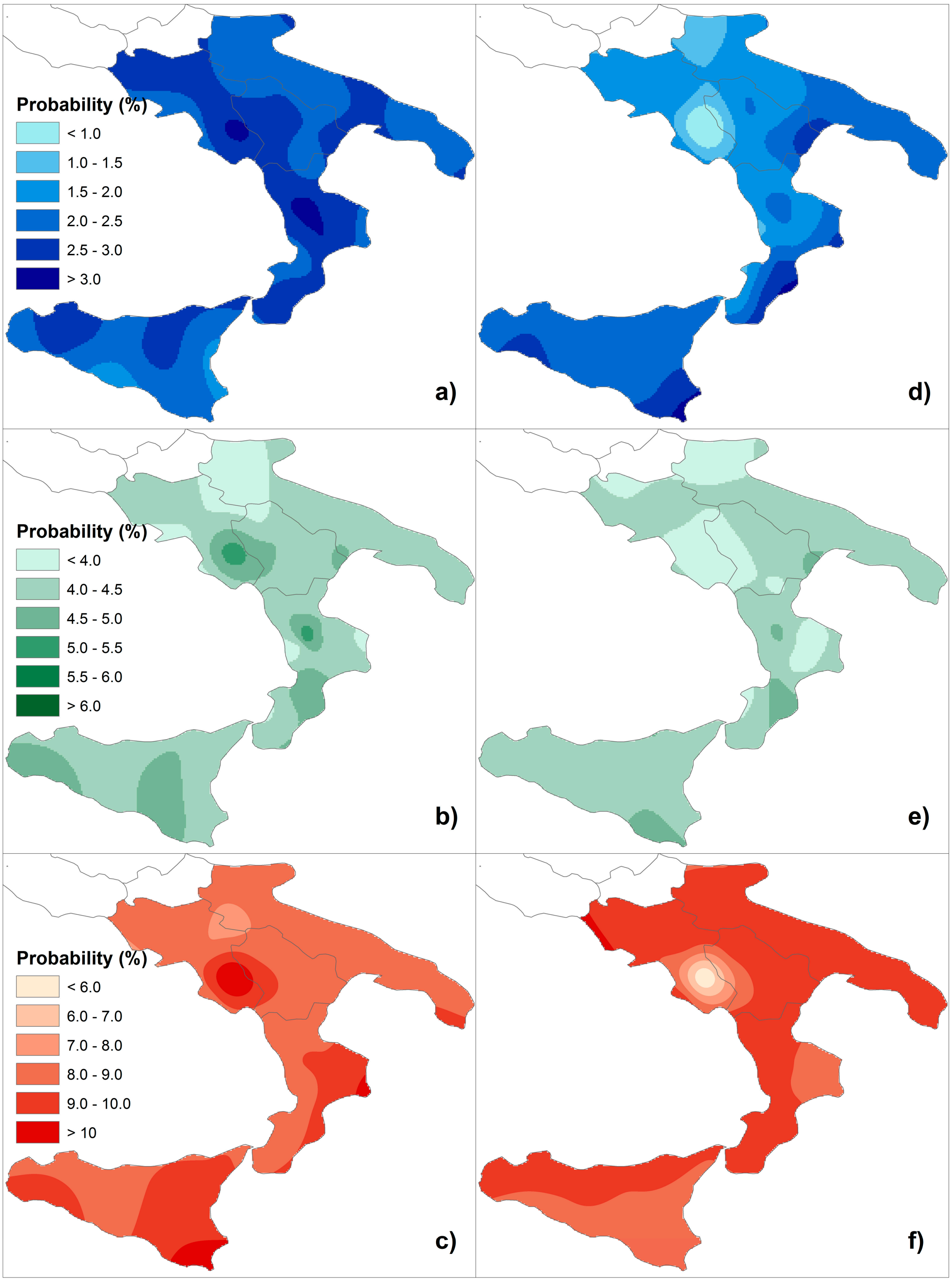

Figure 2. Maps of the monthly occurrence probabilities of Extreme drought (**a**), Severe drought (**b**), Moderate drought (**c**), Extremely wet (**d**), Severely wet (**e**) and Moderately wet (**f**) conditions for the 3-month SPI.

Concerning the extreme drought conditions (Figure 2a), few areas located in the Campania and Calabria regions evidenced probability values greater than 3%, while most of the study area, and particularly the Tyrrhenian side, showed extreme droughts probabilities ranging between 2.5% and 3% (Figure 2a). The areas (Figure 2b) with the highest probabilities of severe droughts (till an occurrence probability of 5.5%) are similar to the ones obtained for the extreme drought conditions, even though most of the study area showed probabilities ranging between 4% and 4.5% (Figure 2b).

As regards the distribution of the occurrence probability of moderate droughts (Figure 2c), the highest values have been evaluated in the Campania region, in the same area where the highest extreme and severe dry values have been identified, and on the eastern and the south-eastern sides of Calabria and Sicily, respectively (Figure 2c). For this drought class, most part of the study area presented probabilities ranging between 8% and 9%. Concerning the occurrence probability distributions of wet conditions (Figure 2d–f), generally opposite results than those referred to dry conditions have been detected. However, there are areas where high probability values were evaluated for both dry and wet conditions which are mainly located on the Ionian side of the Basilicata and the Calabria regions (Figure 2d,e). As a general result, for this short time-scale (3 months), the probabilities of dry conditions are higher than those of wet conditions. This is confirmed by Figure 3, in which the results obtained for both dry and wet conditions, at the various time-scales, are summarized.

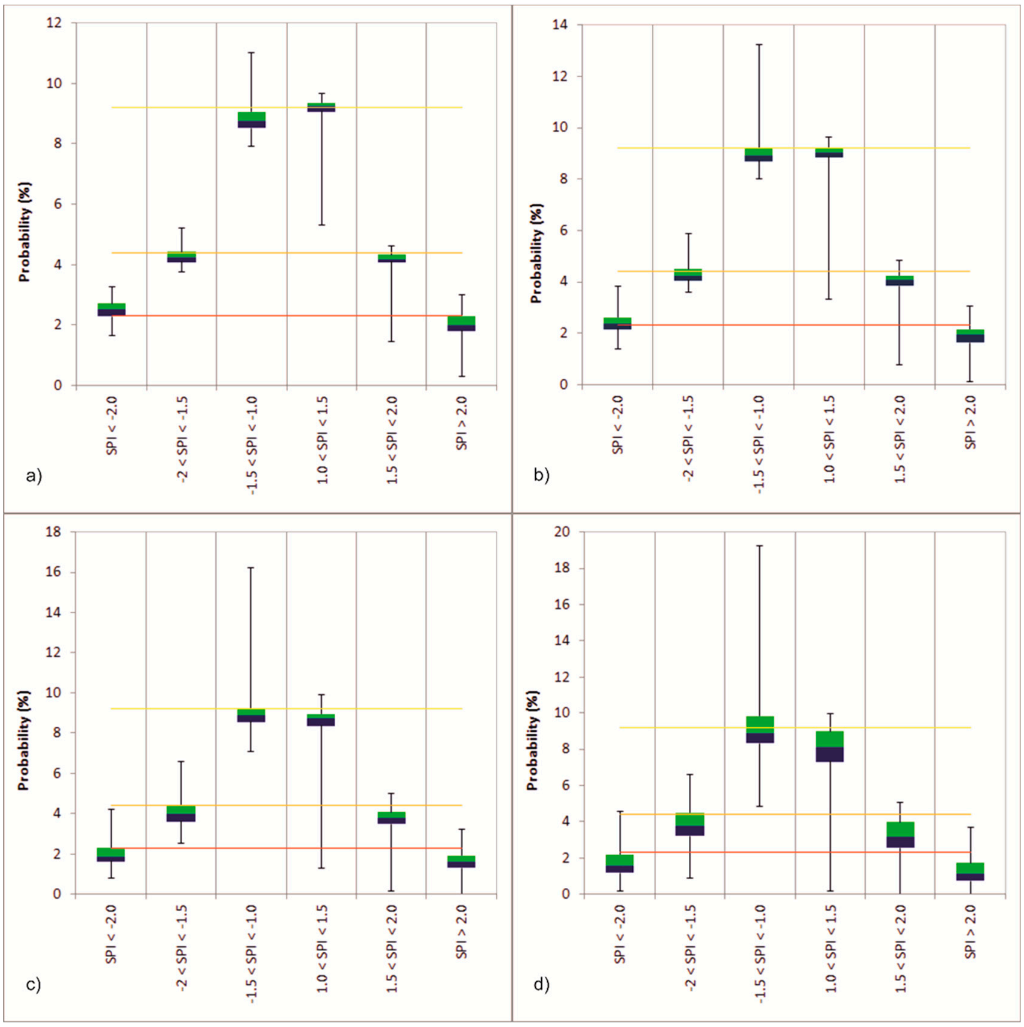

Figure 3. Box-plots of the regional occurrence probabilities of Extreme, Severe and Moderate drought and wet conditions for the 3-month (**a**), 6-month (**b**), 12-month (**c**) and 24-month (**d**) SPI. The lines indicate the theoretical values proposed by McKee et al. [32].

In particular, for the 3-month SPI (Figure 3a), the average probabilities values of the severe and extreme drought conditions are higher than those corresponding to the severe and extreme wet ones. Moreover, the average probability value of the extreme drought condition (about 2.5%) is higher than the theoretical one (2.3%) presented by McKee et al. [32].

Figure 4 shows the results of the occurrence probabilities evaluated for the 6-month SPI.

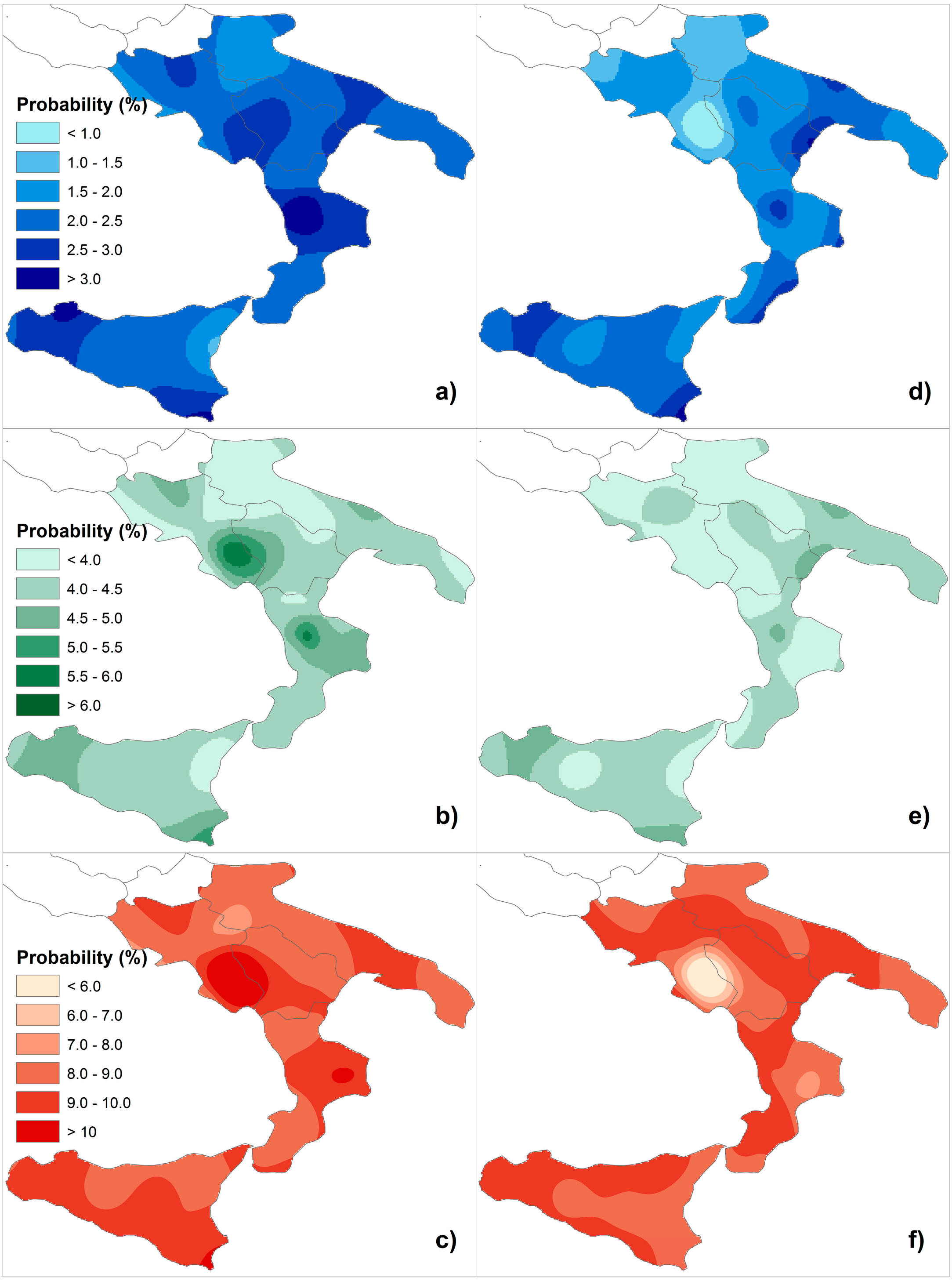

Figure 4. Maps of the monthly occurrence probabilities of Extreme drought (**a**), Severe drought (**b**), Moderate drought (**c**), Extremely wet (**d**), Severely wet (**e**) and Moderately wet (**f**) conditions for the 6-month SPI.

In particular, Figure 4a points out the spatial distribution of the probabilities of extreme droughts. The highest probability values (>3%) have been localized in two small areas of Northern Calabria and Northern Sicily. The spatial probability distribution of severe values (Figure 4b) showed similar results to those evaluated for the 3-month SPI but with higher values, reaching 6% in some areas of Campania and Calabria. Regarding the moderate drought conditions (Figure 4c), most part of the study area presented occurrence probability values ranging between 8% and 9% with the highest probabilities mainly identified in Campania and Calabria (values > 10%).

Also for the 6-month SPI, the extreme and severe wet conditions (Figure 4d,e) showed lower probabilities values than the ones obtained for dry conditions, with the highest values detected only in small areas of Apulia, Basilicata, Calabria and Sicily (between 2.5% and 3%).

Concerning the severe conditions, most of the study area evidenced probability values lower than 4% and between 4% and 4.5%, with Sicily showing probability values higher than the other three regions of the study area. Finally, the moderate wet conditions (Figure 4f) showed high probability values (between 9% and 10%) across almost all the study area and in particular between Apulia and Basilicata, on the Tyrrhenian side of Calabria and in large coastal areas of Sicily. Similar to the 3-month SPI, also for the 6-month SPI (Figure 3b), the average probability values of severe and extreme dry conditions are always greater than the wet ones.

In Figure 5a the spatial distribution of the occurrence probabilities of extreme drought values for the 12-month SPI are shown. The highest probability values (>3%) have been detected in the northern parts of Campania and Apulia, on the Tyrrhenian side of Calabria and on the northernmost and the southernmost areas of Sicily. The majority of the study area presented probability values ranging between 1.5% and 2.5%. Concerning the severe drought, only limited areas in Calabria and Campania presented occurrence probabilities values higher than 6% (Figure 5b), while almost all the study area evidenced occurrence probabilities lower than 4%. As regards the moderate drought conditions (Figure 5c), a large portion of the study area showed probabilities values ranging between 8% and 10%, with the highest values (>10%) located in Calabria, Campania and in the southernmost part of Sicily. Generally, the wet conditions (Figure 5d–f) presented lower probabilities than the dry ones. In particular, while similar results (occurrence probabilities >3%) have been identified in Apulia and in Sicily for extreme wet (Figure 5d) and drought conditions, the severe wet conditions showed very low occurrence probabilities (<4%) for almost all the study area (Figure 5e).

Regarding the moderate wet range (Figure 5f) of the 12-month SPI values, Sicily and Apulia showed the highest probabilities values (between 8% and 10%). Figure 3c shows that for the 12-month SPI the average probability values of the different dry classes are always higher than the wet ones.

Finally, concerning the 24-month SPI, the results of the spatial analysis are shown in Figure 6. The highest probability values for the extreme drought conditions (>3%) have been detected in northern Campania, in the northern Tyrrhenian side of Calabria and in the northernmost and southernmost areas of Sicily (Figure 6a). The majority of the investigated territory presented probability values of severe dry conditions lower than 4%, with only few areas of Campania, Calabria and Sicily, where the probabilities reach values greater than 6% (Figure 6b).

Regarding the moderate dry values for the 24-month SPI (Figure 6c), a large portion of the study area on the Tyrrhenian side, covering parts of the Campania, Basilicata and Calabria regions, showed probability values higher than 10%.

As regards the wet extreme values, a high percentage of the study area presented probabilities lower than 1%. In fact, only two small areas in Sicily evidenced probability values higher than 3% (Figure 6d). Similar results have been obtained for the severe wet conditions (Figure 6e) while for the moderate wet values, the highest probabilities, although lower than 10%, have been detected in Sicily and Apulia. The differences between dry and wet values of the 24-month SPI are clearly summarized in Figure 3d, which confirms that the average probability values of the different dry classes are always higher than the wet ones.

As a summary of the results obtained for the severe and extreme drought conditions, on a short-term the highest probability values have been mainly obtained in few areas located in the Campania and Calabria regions while, considering the long-term, the highest probability values have been detected in the northern parts of Campania, on the Tyrrhenian side of Calabria and on the northernmost and the southernmost areas of Sicily.

The results of this paper confirm that there are more chances for dry conditions than wet conditions [74,75]. This is a critical issue for agricultural areas such as southern Italy, that suffers climate change [76–78] which is a major driver of agricultural and meteorological drought.

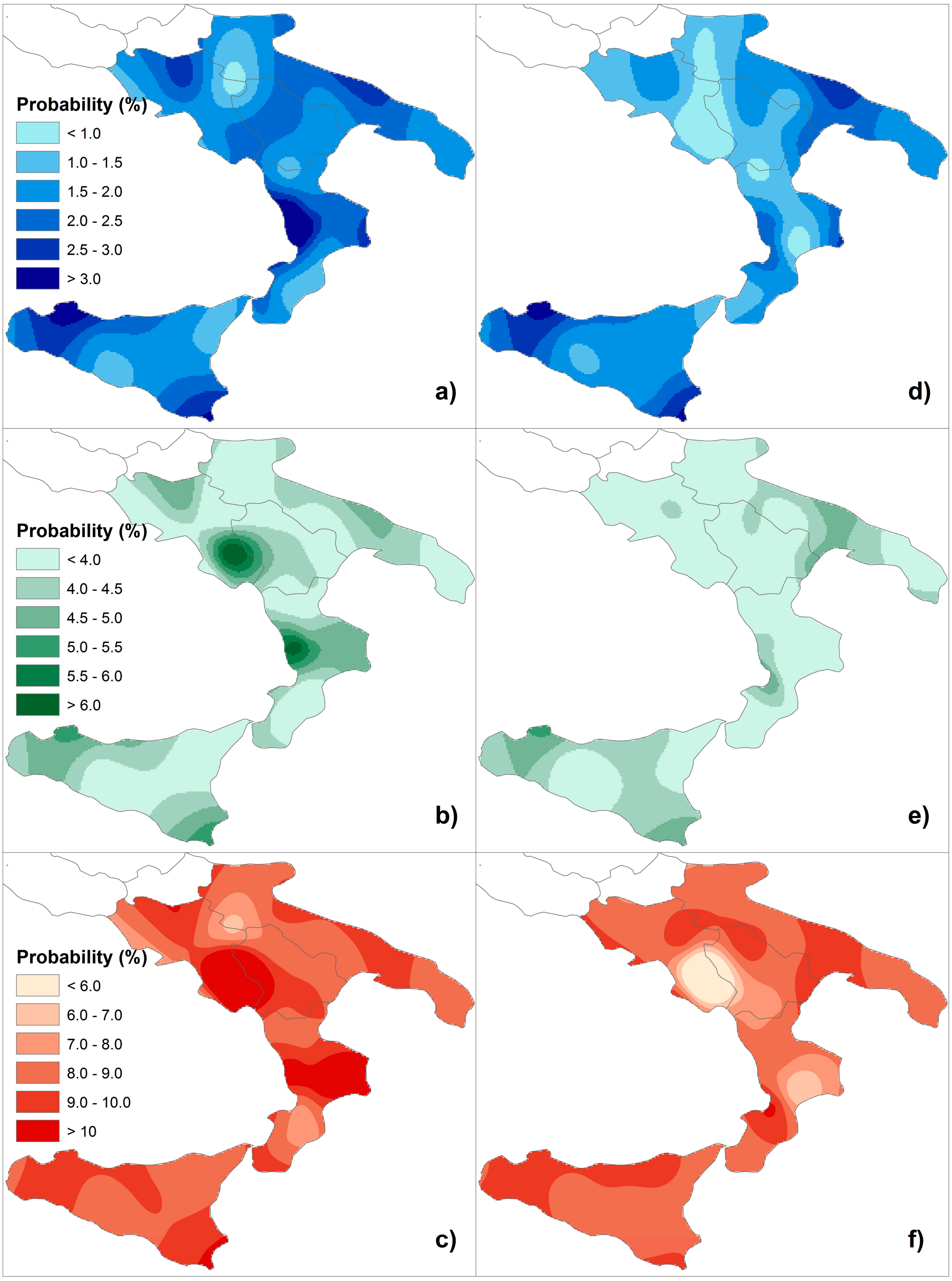

Figure 5. Maps of the monthly occurrence probabilities of Extreme drought (**a**), Severe drought (**b**), Moderate drought (**c**), Extremely wet (**d**), Severely wet (**e**) and Moderately wet (**f**) conditions for the 12-month SPI.

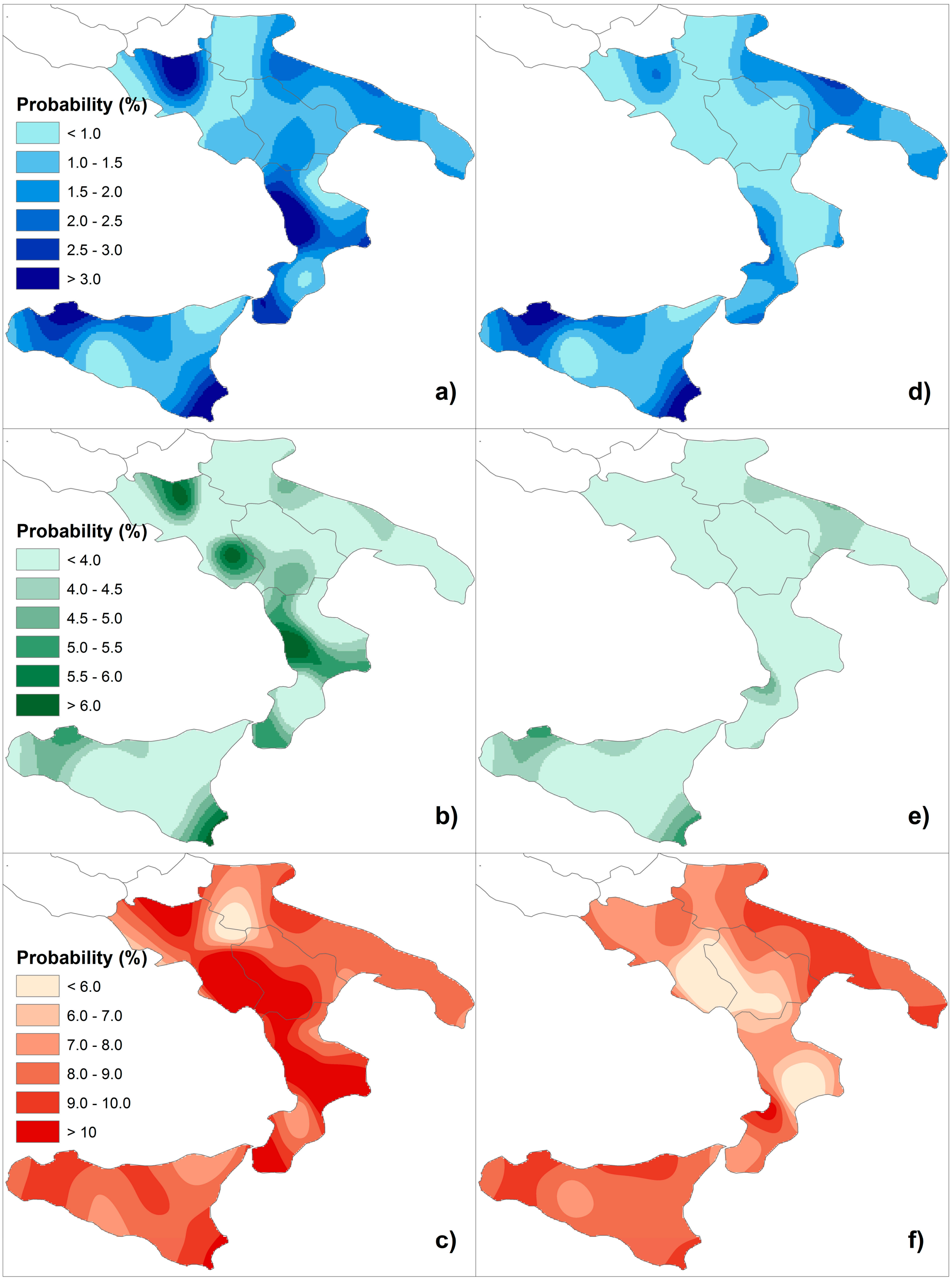

Figure 6. Maps of the monthly occurrence probabilities of Extreme drought (**a**), Severe drought (**b**), Moderate drought (**c**), Extremely wet (**d**), Severely wet (**e**) and Moderately wet (**f**) conditions for the 24-month SPI.

4. Conclusions

The investigation of dry and wet periods in a large area of southern Italy, through the stochastic modeling of 46 monthly precipitation series and the subsequent synthetic generation by means of a Monte Carlo technique, allowed the comparison among the occurrence probabilities of different classes of SPI values, for both short- and long-term periods. The obtained results showed a decreasing tendency of the occurrence probability of both dry and wet conditions when the time scale increases (passing from 3 to 24 months), with the exception of the moderate dry conditions that presented a different behavior. In fact, in a large area partially covering mainly Campania and Basilicata regions, higher than expected probability values for moderate droughts coexist with lower than expected probability values for moderately wet periods, thus evidencing the clear shift towards drier conditions. The results also show some areas where both the dry and wet conditions reach the maximum of probability values, evidencing high variability of precipitation temporal distribution. In general, the average values of occurrence probability both of dry and wet conditions are almost always lower than the experimental McKee values, with the exception of the extreme dry SPI3 values.

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