

## Article

# Karst spring discharge evaluation using a rainfall-input model: the case study of Capodacqua di Spigno Spring (Central Italy)

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**Abstract:** The increasing occurrence of widespread drought phenomena is a global environmental emergency, especially for the effects of ongoing climate change on groundwater availability. Dry years and extreme temperatures are common drivers of current climate impacts all over the world, including, for example, freshwater supply for drinking and agriculture purposes, ecosystems, forestry, health, etc.. In this frame, to ensure temporal water availability in water-stressed areas, a sustainable groundwater management is an increasing challenge. Most of groundwater in the South-East Latium Region, Central Italy, as in the whole Apennine Mountains chain, is stored in karst aquifers. In this area important water resources are present, but even here in the last decades they are affected by groundwater depletion as a consequence of occurring drought events, the upward trend in the globally average temperature and the increasing of anthropogenic activities. Due to the lack of flow rates data of springs in many areas of Italy, the spring response modeling could be a useful tool for supporting a proper water resource management. Several research studies proposed methods based on relationships between spring discharges and rainfall data. The goal of this paper is to propose a model, based on rainfall-discharges cross correlations, in order to assess the spring flow rate patterns of Capodacqua di Spigno Spring, which is the main one in the study area. The results obtained using the developed model has been compared to an existing method that uses the SPI index for the estimation of the minimum annual spring discharge.

**Keywords:** karst spring, groundwater, discharge modelling, water management.

## 1. Introduction

Water crises are more and more frequent in the last years. Changes in global climate seem to affect the hydrological cycle, altering surface water levels and groundwater recharge to aquifers with various other associated impacts on natural ecosystems and human activities. In this scenario, it seems clear to affirm that climate change can impact on groundwater resources by modifying the renewable portion of groundwater storage through changes in recharge [1]. Various studies with different approaches at the river basin level determined the effect of climate change on water resource systems. The main conclusions of these publications are that there will be less surface runoff and aquifer recharge due to increasing temperatures, and decreasing or increasing precipitation [2].

During the Mediterranean long dry summer months, karst springs provide fresh and high quality water, which has been an important resource for human development in this region since antiquity [3]. Specifically, in Italy, karst carbonate aquifers of the Central Apennines represent the larger groundwater resource [4].

In order to plan a sustainable water resource exploitation, an appropriate water quantitative evaluation is necessary, monitoring spring discharge during the whole hydrological year. When

spring flow measurements are not possible to carry out and there is not an appropriate knowledge about long time discharge series, spring discharge estimation is recommended. Many approaches have been proposed to analyze the relations between the rainfall time series over the recharge area and the spring outflow [5]. These models, for example, are based on continuous and discrete wavelet analysis [6,7], cross-correlation analysis [8,9,10], or machine learning models [11]. Other studies, concerning karst springs, have employed time-series analysis studying transfer function between rainfall and spring discharge, obtained by black-box models [12] or artificial neural network [12]. Unlike typical hydrologic models, data-driven approaches do not rely directly on explicit physical knowledge of the process, but they build a purely empirical model based on observed relationships between input and output variables. Using various learning algorithms data-driven approaches provide a flexible way to model complex phenomena such the spring discharge [14].

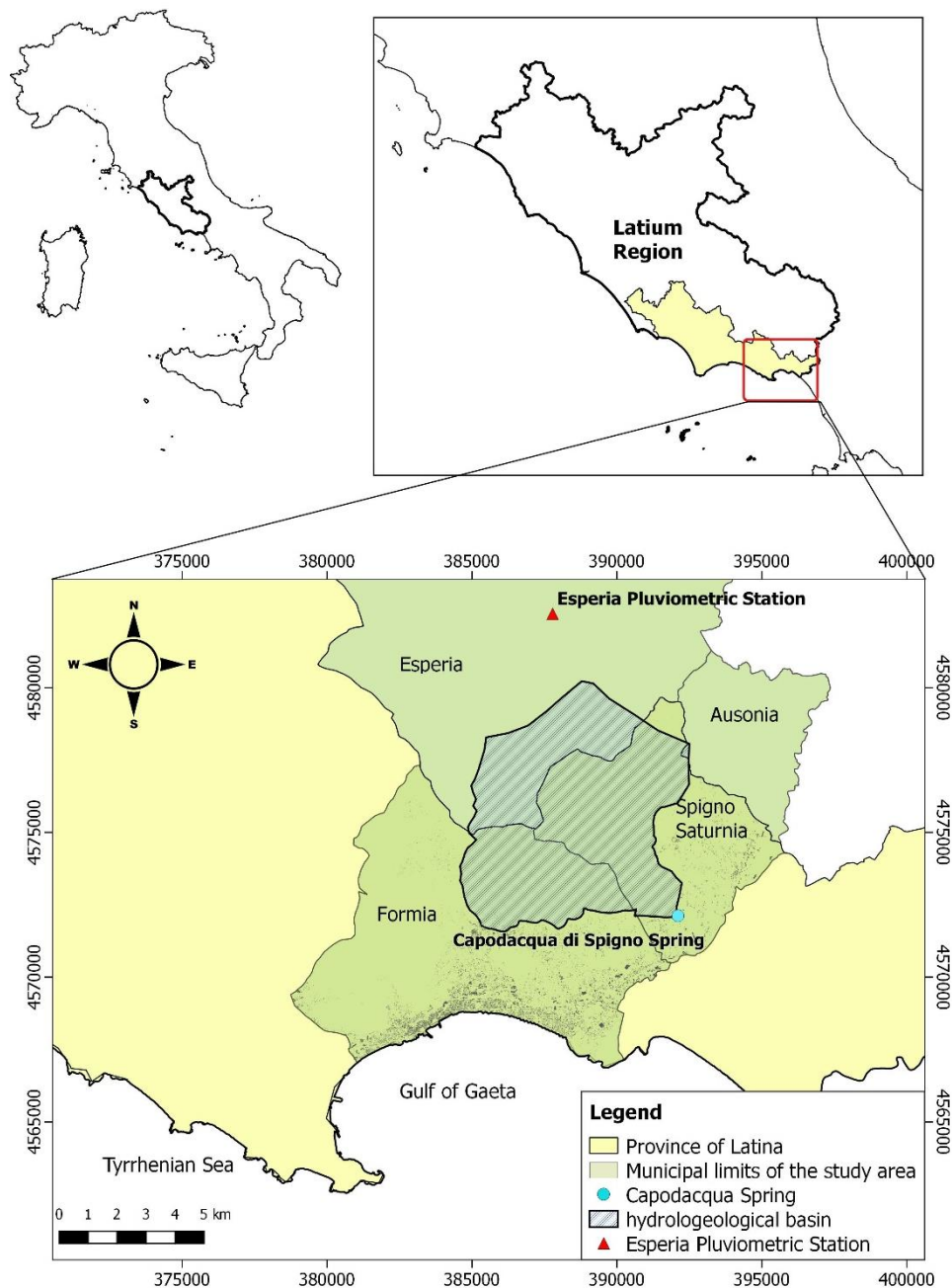
The present research concerns the development of an estimation model, based on data-driven approaches, to evaluate spring discharge. The proposed model is grounded on statistical correlations between the series of monthly spring discharge values and the series of monthly rainfall values, referred to the same time series. Specifically, the present approach is represented by a linear cross-correlation model, whose input data needed, after the initial training, are only the rainfall data. The present study represents, therefore, the first results of an approach that tries to disengage from the flow rate values as input, in estimating the karst spring discharge.

Afterwards, the model was applied to the Capodacqua di Spigno Spring, calibrating it on the available flow data, related to the years 1973-1977, as part of a scientific technical collaboration between the water agency Acqualatina S.p.A. and Sapienza University of Rome.

The proposed model is compared to an existing and consolidated forecasting method that uses the SPI index for the estimation of the minimum annual spring discharge, a method already widely used in Italy and in many other countries [5,8]. The SPI analysis is often used internationally to study and characterize the hydrological drought [15, 16,17,18]. The SPI is an indicator of the deviation from the mean of the cumulative rainfall over a specific time-interval, reflecting periods of low (negative SPI) or abundant precipitation (positive SPI). These hydrological conditions are transferred into the aquifers, by lowering or rising groundwater levels and by decreasing and increasing spring discharges [19]. The SPI was designed to quantify the precipitation deficit for multiple timescales. These timescales reflect the impact of drought on the availability of the different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale. Groundwater, streamflow and reservoir storage reflect the longer-term precipitation anomalies [20].

## 2. Geological and Hydrogeological Setting of the Study Area

In this study, Capodacqua di Spigno Spring, one of the main karst in the Southeast Latium Region, has been studied in order to test a method for spring discharge evaluation, on the basis of rainfall data. The Capodacqua di Spigno Spring hydrogeological basin involves the competence territory of Spigno Saturnia, Formia and Esperia municipalities, in the province of Latina (Figure 1).



**Figure 1.** Territorial framework of the study area.

The study area is located in the Western Aurunci Mountains, which together with the Lepini and the Ausoni Mountains belong to the Pre-Apennines of Latium and form the carbonatic platform of the Volsci Ridge, separated from the Apennine ridge by the Latina Valley [21].

The Western Aurunci hydrogeological unit, mostly made of dolomitic limestone and dolomites of Jurassic and Cretaceous age [21,22,23,24] hosts an important karst aquifer, which give rise to many karst springs, including Capodacqua di Spigno Spring, one of the most important water resources in the Southern Latium Region used for drinking supplies.

The Capodacqua di Spigno Spring, located at an altitude of about 35 m a.s.l., is the natural outcrop of groundwater discharging from a hydrogeological basin of about 60 km<sup>2</sup> [1]. The spring water comes out from the permeable limestone of La Civita Mountain and Castello Mountain and flows above the upper Miocene clays, at the lowest point of the limestone-clay contact [25].

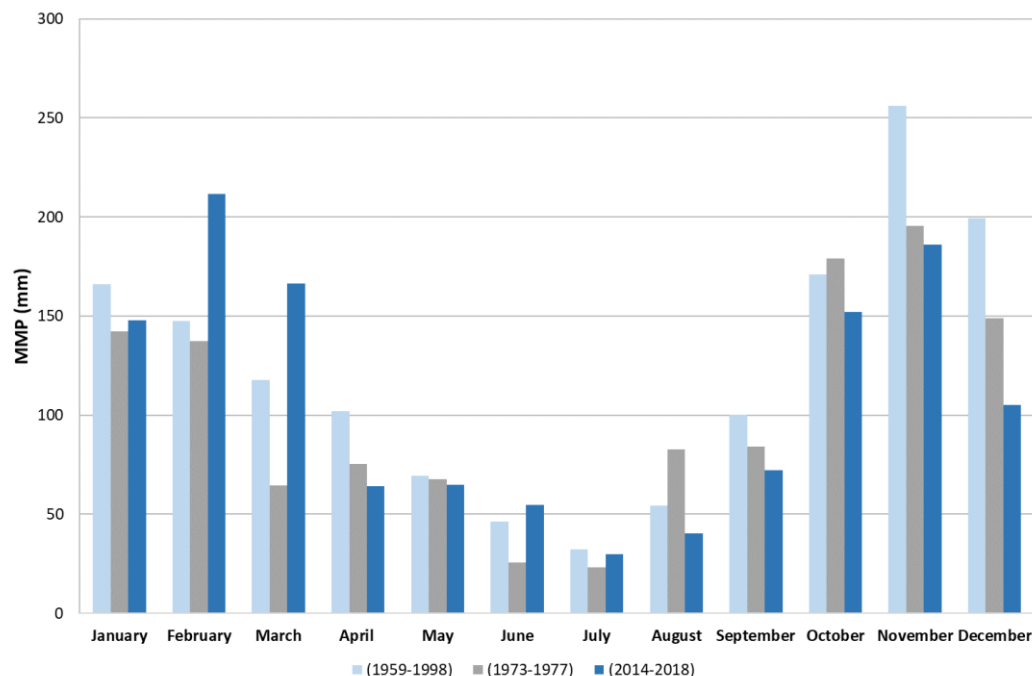
The altitude of the Capodacqua di Spigno hydrogeological basin ranges from about 100 m a.s.l. to about 1500 m a.s.l., with an average value of 880 m a.s.l. [1]. The general groundwater flow direction

of the aquifer is towards SE, but there are also important local flows along the two faults that delimit the carbonatic series outcropping, especially the one to the east, which seems to represent the main water conduit towards the spring [26].

Carbonate dissolution strongly influence groundwater flow and evolve into complex networks throughout the limestone matrix. The most important karst landforms are ruttled fields, Karren, sinkholes, and swallow holes. The high permeability of the karst surface is responsible of the rapid infiltration of rainfall into the aquifer by the karst depressions (superficial and sub-surficial) originate from the carbonate dissolution processes related to the contact between rainwater and carbonate rocks; i.e. the limestone, the dolomitic limestone and the dolomites, which are part of the Capodacqua di Spigno Spring hydrogeological basin. Although dolomite has a lower solubility than calcite, in the series the two minerals alternate, so in the studied area the superficial karst forms are widespread in the hydrogeological basin, except in those areas with high slopes, usually associated with the fault lines.

The climatic assessment of the study area has been evaluated on the basis of rainfall monthly time series collected in the Esperia rainfall gauge, the closest to the recharge area of the spring in the northern part of the hydrogeological basin (Figure 1). However, rainfall values from 1998 to 2014 are not available for this Pluviometric Station. Therefore, the rainfall behavior for the longest time series available, i.e. from 1959 to 1988, was studied. The two precipitation time series used to perform, first, the model training (time window 1973-1977) and, afterwards, the validation of the cross-correlation model (time window 2014-2018), were also analyzed.

The Mean Annual Precipitation (MAP) of the time series range from 811 to 2103 mm/year in the period 1959-1998. The rainfall seasonal trend (Figure 2) shows that the most important contribution is due to the rainiest season (from November to February), with a trend inversion in the last five years (2014-2018), where it has been registered a deficit mostly due to a reduced contribution of winter rainfall in November and December and a positive increase in February and March.

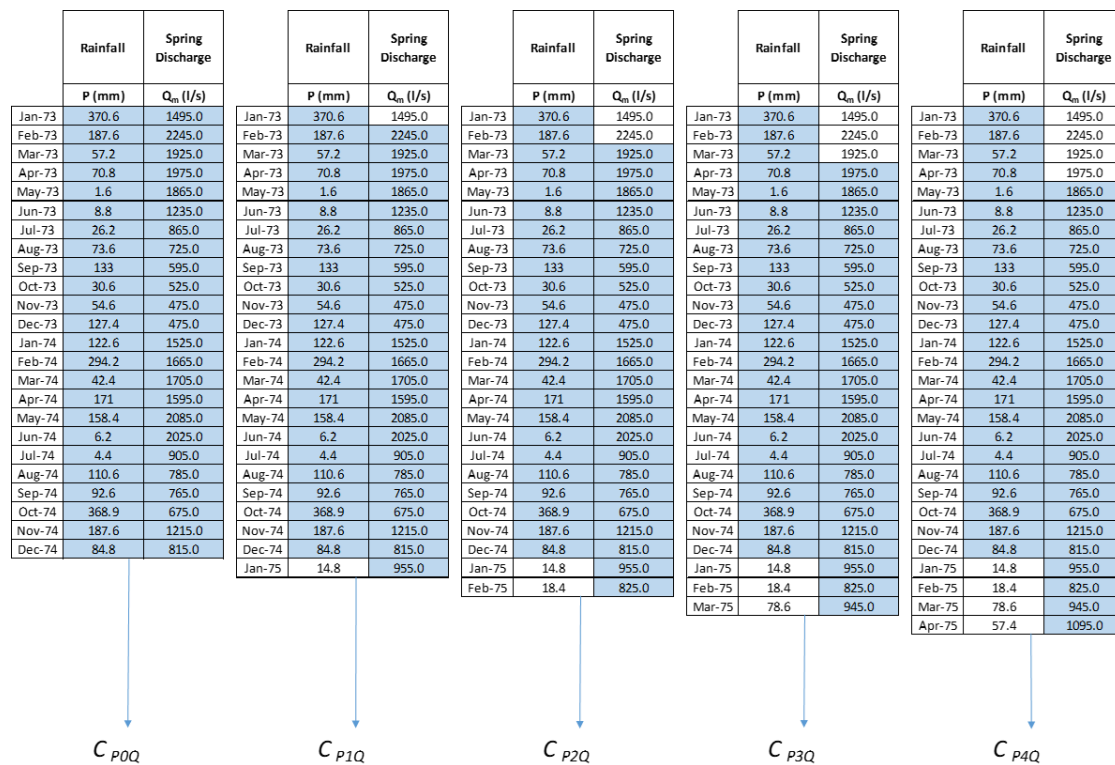


**Figure 2.** Mean Monthly Precipitation (MMP) seasonal trend in the study area.

### 3. Materials and Methods

The proposed model is based on cross-correlations between the monthly spring discharge series and the series of monthly rainfall values, referred to the same period (at least 3 years).

Cross-correlations are carried out "backwards". Thereby, it is possible to determine a correlation coefficient ( $C_{PiQ}$ ) which may numerically define the incidence of previous monthly rainfall data on the spring flow value related to the specific month considered (Figure 3).



**Figure 3.** Graphical representation of the  $C_{PiQ}$  correlation coefficients determination.

In such a way, on a different time window, it is possible to obtain an estimated value of the spring flow rate as the sum of different contributions, multiplied by an amplification coefficient ( $k$ ), which will be typical of the specific hydrogeological basin of the spring object of study.

More specifically, each contribution is expressed by the rainfall value of the  $i$ -th month (generally from the same month up to the previous 6 months) multiplied by the  $i$ -th coefficient obtained from the correlation. The formula used to estimate spring discharges is the following one:

$$Q_0 = k \cdot \left[ \sum_{i=-n}^0 P_i \cdot C_{PiQ} \right] \quad (1)$$

Where:

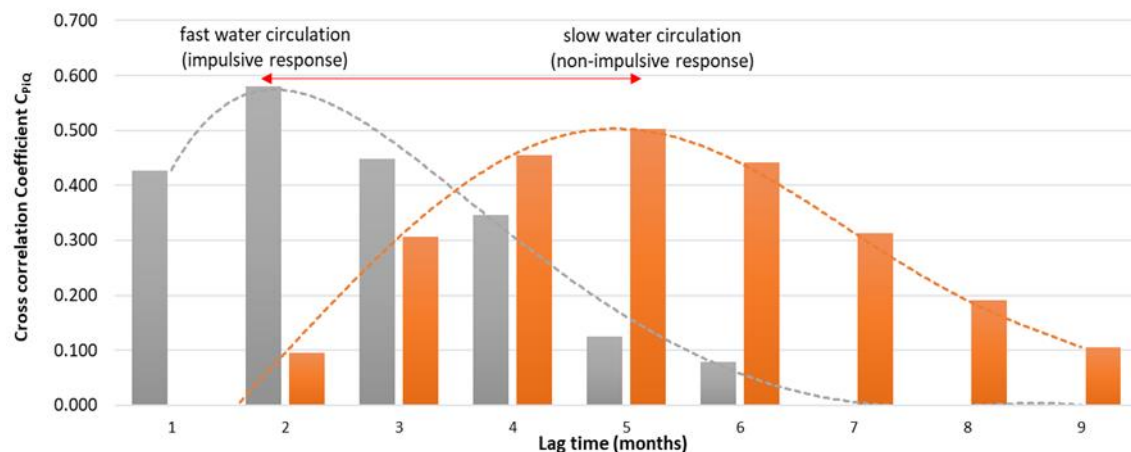
- $Q_0$  is the spring flow rate referred to the specific month taken into account (l/s);
- $k$  is an amplifying or reducing factor from rainfall to discharge values and is representative of each spring and its hydrogeological basin;
- $P_i$  is the rainfall data (in mm) of the thermo-pluviometric station representative of the hydrogeological basin related to the specific month, with  $i$  that varies from the  $n$ -th preceding month up to the reference month ( $i = 0$ );
- $C_{PiQ}$  is the correlation coefficient between the spring flow data series and the rainfall data series (for  $i$  varying from  $n$  to 0);

The  $n$  value represents the general behaviour of the spring feeding aquifer. In fact, karst aquifers may have three types of groundwater circulation, related to different types of permeability (porosity, cracking and karst conduits).



Karst conduits hydraulic conductivity is associated with a fast circulation of groundwater in the aquifer, which implies an impulsive response of the spring flow to the rainfall inputs.

This phenomenon influences the values of the correlation coefficients, between rainfall data and spring flow values. Springs with a fast response to the hydrological input show the highest correlation coefficients in those months with shortest lag time (i.e. temporally "closer" to the output specific month). On the contrary, those with a slower response show the opposite behaviour (Figure 4).



**Figure 4.** Two examples of cross-correlation between the monthly rainfall series and the discharge series related to two different springs.

For the testing method, the only time series available was 5 years long (1973-1977). In this period, spring discharges values were due to measurements carried out on a monthly basis ( $Q_m$ ). Other measurements were carried out, before 1973, but the discharge time series was not continuous and for this reason it was not possible to use it for the model training, which consisted in the determination of cross correlation coefficients.

Rainfall data ( $P$ ) taken into account are those collected by the pluviometric station of Esperia, which is the only one located nearby the spring hydrogeological basin and whose data temporally matched spring flow measurements (Table 1).

**Table 1.** Rainfall and Capodacqua di Spigno Spring discharges data for the model training period.

	1973		1974		1975		1976		1977	
Month	P (mm)	$Q_m$ (l/s)	P (mm)	$Q_m$ (l/s)	P (mm)	$Q_m$ (l/s)	P (mm)	$Q_m$ (l/s)	P (mm)	$Q_m$ (l/s)
January	370.6	1495	122.6	1525	14.8	955	27.2	1015	176.4	4170
February	187.6	2245	294.2	1665	18.4	825	111.8	1015	74.4	3270
March	57.2	1925	42.4	1705	78.6	945	109.2	1130	35.6	1850
April	70.8	1975	171	1595	57.4	1095	57.2	1265	20	1800
May	1.6	1865	158.4	2085	55.2	945	83.6	1115	40.4	1744
June	8.8	1235	6.2	2025	15.2	795	52.2	1115	45.8	1230
July	26.2	865	4.4	905	30.6	535	33.6	965	21.2	960
August	73.6	725	110.6	785	108.4	400	35	535	85.8	645
September	133	595	92.6	765	40.4	370	73.2	525	81.2	643
October	30.6	525	368.9	675	145	265	288	515	62.6	878
November	54.6	475	187.6	1215	242.4	310	406	1925	86.8	600
December	127.4	475	84.8	815	143	515	308	3815	81.4	926

4. Results and discussion

Spring discharge and rainfall data have been previously used in the model training for the determination of correlation coefficients (Table 2).

The time series analyzed for the training was 5 years long (1973-1977). In this period, spring discharges values were available due to measurements carried out on a monthly basis.

Results highlight an impulsive behavior of Capodacqua di Spigno Spring. The highest values of cross correlation coefficients are referred to  $i = 1$  and  $i = 2$  (respectively equal to 0.59 and 0.60). The spring response to rainfall show a short lag time, which is typical of "dominant drainage network" karst aquifer behavior, with groundwater circulation mainly occurring in the karst conduits. The amplifying factor from rainfall to discharge values ( $k$ ), founded through a goal seek, is equal to 5, denoting a large hydrogeological basin.

Table 2. Cross-correlation coefficients for Capodacqua di Spigno Spring.

$i = -5$	$i = -4$	$i = -3$	$i = -2$	$i = -1$	$i = 0$
$C_{PiQ}$					
0.17	0.33	0.48	0.60	0.59	0.21
$k \cdot C_{PiQ}$					
0.83	1.64	2.42	2.99	2.93	1.04

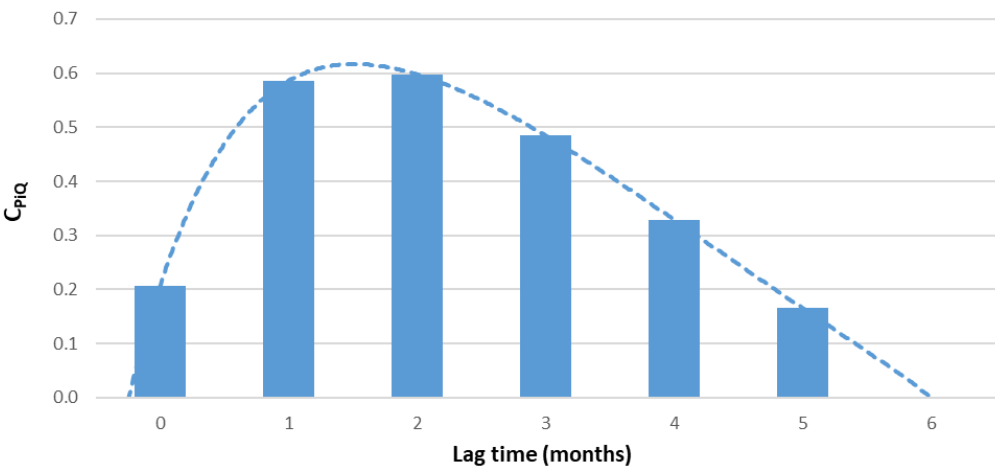
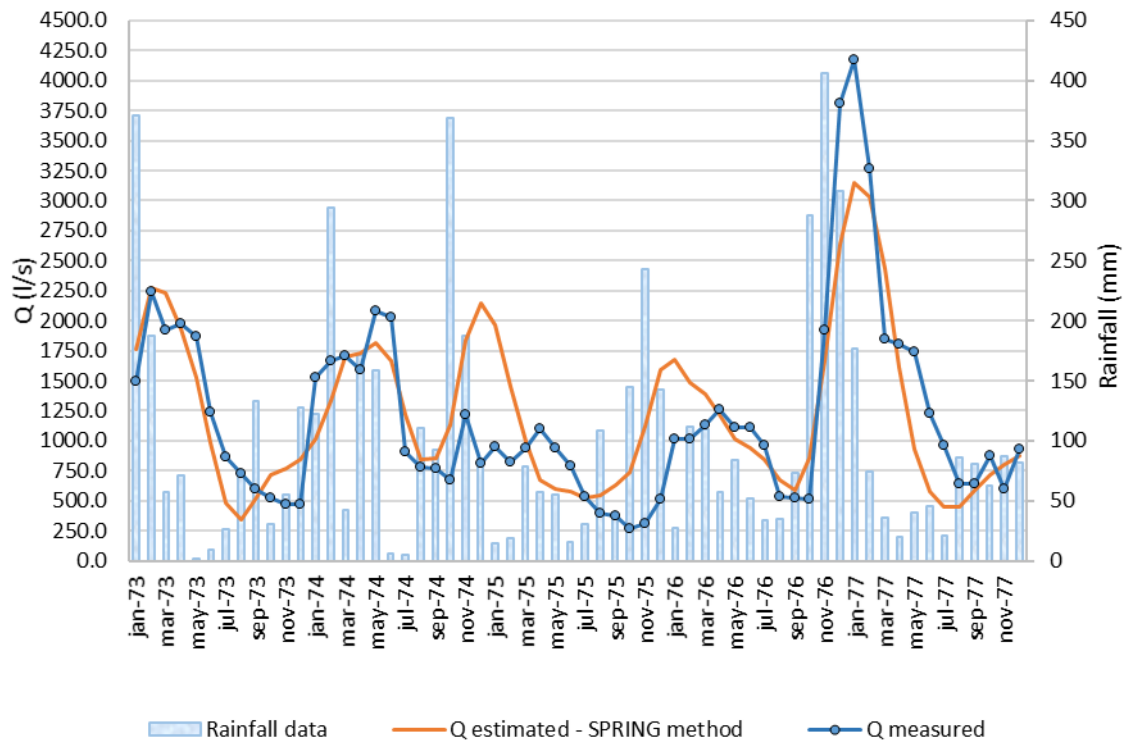


Figure 5. Cross-correlation coefficients distribution for Capodacqua di Spigno Spring obtained for the training period (1973-1977).

Applying equation (1) to rainfall data, the estimated flow rates obtained were compared with the measured ones in the same training time window. The blue line represents the measured values ( $Q_m$ ), while the estimated flow rates trend obtained is described by the orange line ( $Q_e$ ), showing a good fitting (Figure 8).



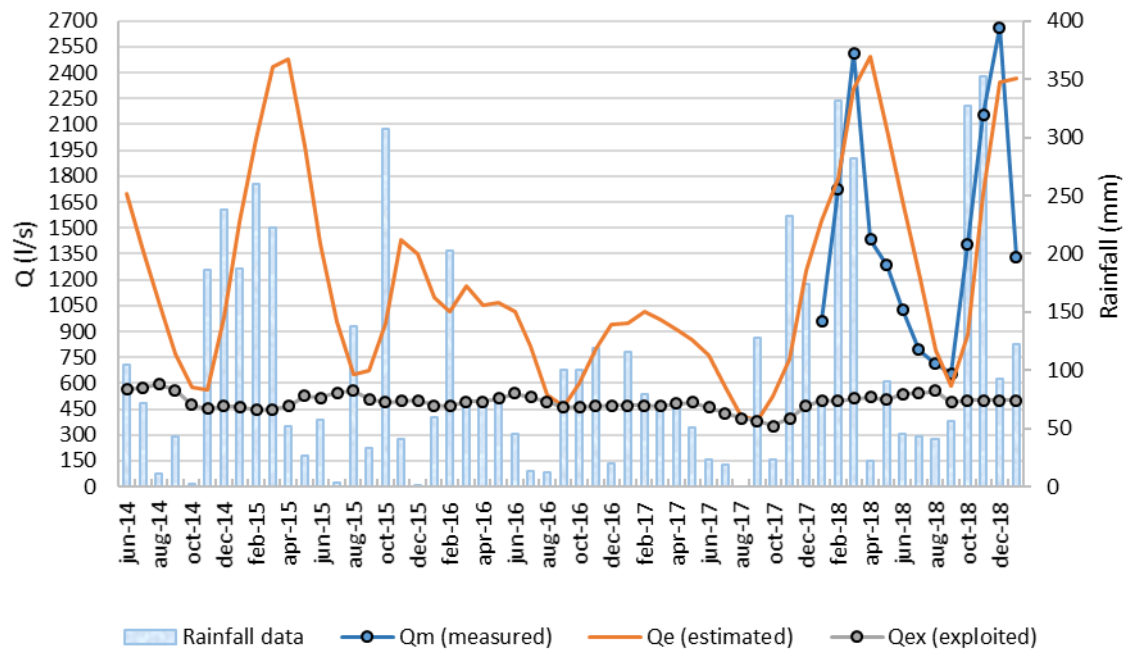
**Figure 6.** Training time window: comparison between estimated ( $Q_e$ ) and measured ( $Q_m$ ) discharges for Capodacqua di Spigno Spring.

Afterwards, following the same way, equation (1) was applied to input rainfall data referred to the last few years (2014–2018), in order to study possible spring discharge changes and test the reliability of the model. Two anomalies in spring flow rates, related to the drought events of 2016 and 2017, are successfully described by the estimated flow trend.

In the time window considered (validation time window), the measured flow rate data ( $Q_m$ ) are not available until January 2018 onwards, i.e. when the DICEA started the quantitative spring monitoring activities. These activities mainly consisted in measurements of the excessing spring flow rate in a discharge channel.

For the previous years, only the withdrawal rates ( $Q_{ex}$ ), carried on by the local water supply agency (Acqualatina S.p.A.) are available. Nevertheless, the withdrawal trend was very useful for assessing the correct estimation of the minimum spring discharges during the drought events. In fact, the withdrawal trend, which values is around 500 l/s, intensively dropped during the drought events of 2016 and 2017. In these cases, the flow rate available at the spring was assumed to be equal to the withdrawal. The phenomenon is well represented by the estimated discharge values, plotted in Figure 7. All values obtained with the proposed method fall upon the  $Q_{ex}$  values, representing the withdrawal flow rates. Moreover, assuming that the total spring discharge is equal to the sum of excessing flow measurements and the withdrawal values, measurements carried out during 2018 confirms the potentiality of the method: maximum and minimum estimated values of the studied spring discharge ( $Q_e$ ) show a very good accuracy with collected data (Figure 7).





**Figure 7.** Validation time window: comparison between model estimated ( $Q_e$ ), measured ( $Q_m$ ) discharges for Capodacqua di Spigno Spring and the flow rate exploited ( $Q_{ex}$ ) by the local water supply agency (Acqualatina S.p.A.)

At last, minimum discharge values obtained using equation (1) were compared to minimum flow rates estimated using a methodology proposed by Romano et al. (2013) [5] and applied to the case study, using the SPI (Standard Precipitation Index) as input data. This method has been suggested by several Italian regions for the minimum spring discharge forecasting. It is indeed indicated in the 2018 guidelines concerning drought and water scarcity indicators [27], drafted by ISPRA (Italian Environmental Protection Agency) and is internationally recognized.

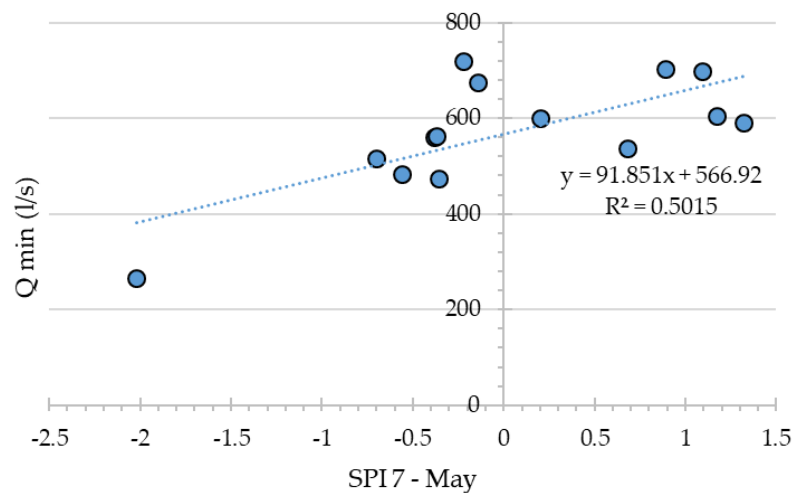
For Capodacqua di Spigno Spring, the reference pluviometric station is Esperia, for which an historical series of monthly precipitation of about 30 years was available. Input data have been used in the SPI calculation, for each month of the year, and for different aggregation scales (SPI1, SPI2 ...SPI24). SPI values were obtained using the "SPI Generator" free software (<https://drought.unl.edu/droughtmonitoring/SPI/SPIProgram.aspx>) (Version release date: 2018-09-06) made available by the National Drought Mitigation Center - UNL.

Besides, the minimum annual flow ( $Q_{min}$ ) of the total discharge series available (years 1964-1977) was identified. In this case, in fact, it was not necessary to have a continuous monthly data series, but only the annual minimum values. Correlation coefficients were calculated, for each month, between the values of the different SPI and the annual  $Q_{min}$ : the correlation matrix was set up and the best correlation was consequently identified (Figure 8)

	CORRELATION MATRIX SPI - Q <sub>min</sub>													
	spi 1	spi 2	spi 3	spi 4	spi 5	spi 6	spi 7	spi 8	spi 9	spi 10	spi 11	spi 12	spi 18	spi 24
January	0.51	0.53	0.53	0.36	0.42	0.43	0.44	0.45	0.38	0.33	0.30	0.17	0.46	0.50
February	0.54	0.61	0.63	0.68	0.53	0.59	0.59	0.59	0.59	0.53	0.49	0.45	0.54	0.59
March	0.05	0.36	0.51	0.55	0.63	0.52	0.58	0.58	0.57	0.57	0.52	0.48	0.52	0.61
April	0.34	0.21	0.42	0.52	0.57	0.67	0.56	0.63	0.62	0.61	0.61	0.57	0.45	0.61
May	0.40	0.51	0.35	0.49	0.56	0.61	0.71	0.60	0.67	0.66	0.65	0.65	0.52	0.60
June	-0.04	0.28	0.56	0.37	0.50	0.58	0.60	0.70	0.59	0.66	0.66	0.65	0.44	0.60
July	-0.18	-0.14	0.17	0.46	0.32	0.46	0.55	0.58	0.68	0.58	0.66	0.66	0.37	0.59
August	-0.39	-0.34	-0.37	-0.15	0.17	0.13	0.31	0.45	0.50	0.61	0.52	0.60	0.47	0.55
September	0.57	0.29	0.24	0.24	0.43	0.49	0.38	0.50	0.55	0.56	0.66	0.56	0.56	0.58
October	-0.12	0.27	0.15	0.14	0.14	0.21	0.30	0.27	0.37	0.49	0.56	0.66	0.61	0.46
November	0.09	0.05	0.26	0.18	0.16	0.16	0.21	0.27	0.25	0.34	0.45	0.51	0.61	0.52
December	-0.34	-0.16	-0.12	0.06	-0.01	-0.01	-0.02	0.03	0.10	0.10	0.19	0.31	0.48	0.35

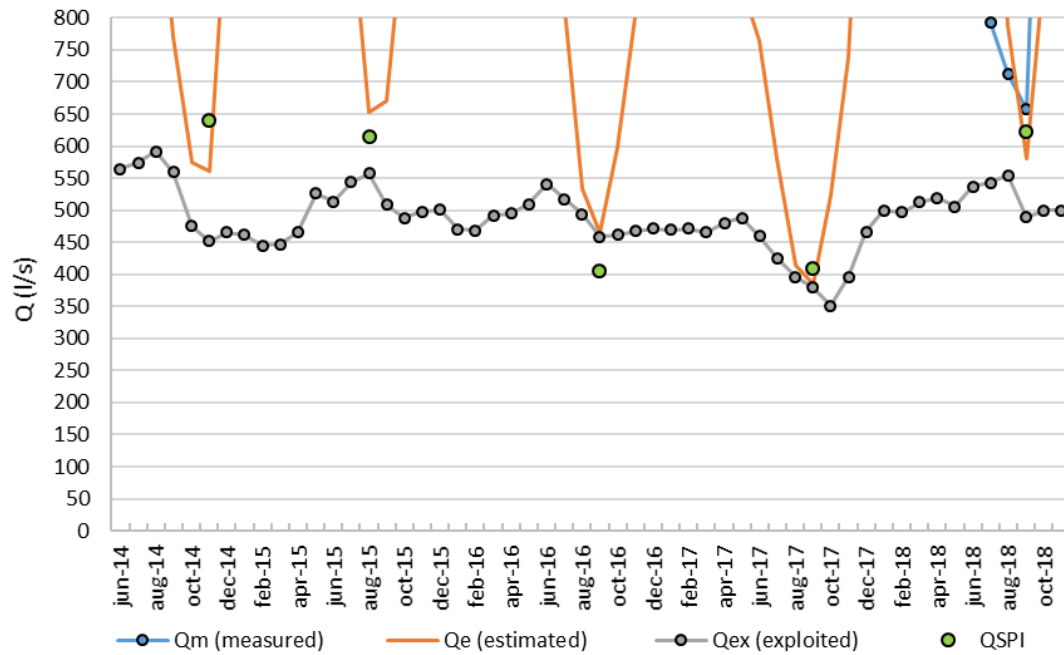
Figure 8. Correlation matrix SPI - Q<sub>min</sub>.

The best correlation found is between the  $Q_{min}$  and SPI7 May, with a  $R^2$  of about 0.5. The linear relationship obtained allowed to extend the  $Q_{min}$  estimation to the validation time window and hopefully to forecast minimum discharges of the studied spring in future water crises (Figure 9).

Figure 9. Relationship between  $Q_{min}$  of the historical discharge series and SPI7-May.

The minimum annual value spring discharge, estimated by the exposed methodology, were plotted with the total discharge series modeled using equation (1).

Figure 10 represents the detailed comparison between these two methods: results show that minimum discharge values are comparable. Generally, Capodacqua di Spigno Spring minimum discharges occur at the end of the summer season (September), with values higher than 500 l/s. The two anomalies, due to the drought events (2016-2017) are well represented by the SPI method as well as the proposed model, whose minimum values, moreover, match well with the flow rates exploited by the local water agency Acqualatina S.p.A. for drinking purposes, which wasn't enough for satisfying civil water networks supply demand.



**Figure 10.** Validation time window: detail on minimum discharges estimated using the proposed model and the minimum annual discharge estimated ( $Q_{SPI}$ ) using the methodology proposed by [27].

In the year 2017 the discharge exploited by Capodacqua di Spigno Spring, during the drought event, dropped to about 380 l/s due to the low supply of the water resource. In this regard, the relative error was calculated between the estimated minimum flow rate and the minimum exploited flow rate, which corresponds to the minimum spring supply. Table 3 shows that for 2017, the discharge estimated with the proposed method ( $Q_e$ ) and with the SPI method ( $Q_{SPI}$ ), compared with the exploited flow rate ( $Q_{ex}$ ), lead to very low relative errors:  $\varepsilon_e = 1.35\%$  and  $\varepsilon_{SPI} = 7.73\%$  respectively.

The formulas used to calculate relative errors are the following ones:

$$\varepsilon_{e(2017)} = \left| \frac{Q_e - Q_{ex}}{Q_{ex}} \right| \cdot 100 \quad (2.1)$$

$$\varepsilon_{SPI(2017)} = \left| \frac{Q_{SPI} - Q_{ex}}{Q_{ex}} \right| \cdot 100 \quad (2.2)$$

Where:

- $Q_{ex}$  = exploited discharge;
- $Q_e$  = estimated discharge;
- $Q_{SPI}$  = estimated discharge with SPI index.

**Table 3.** Comparison between exploited discharge ( $Q_{ex}$ ), estimate discharge ( $Q_e$ ) and estimated discharge with SPI index ( $Q_{SPI}$ ).

September 2017				
$Q_{ex}$	$Q_e$	$\varepsilon_{e(2017)}$	$Q_{SPI}$	$\varepsilon_{SPI(2017)}$
(l/s)	(l/s)	(%)	(l/s)	(%)
379.6	384.7	1.3	408.9	7.7

As previously mentioned, for the year 2018, instead, it was possible to compare the estimated flow rates using both methods considered ( $Q_e$  and  $Q_{SPI}$ ) with the discharge values measured during

DICEA monitoring activities. The relative error between the estimated minimum flow rate using both methods is referred to the minimum measured flow rate. Table 4 shows that even for the year 2018 values of error are quite low.

The formulas used to calculate relative errors are the following:

$$\varepsilon_{e(2018)} = \left| \frac{Q_e - Q_m}{Q_m} \right| \cdot 100 \quad (3.1)$$

$$\varepsilon_{SPI(2018)} = \left| \frac{Q_{SPI} - Q_m}{Q_m} \right| \cdot 100 \quad (3.2)$$

Where:

$Q_e$  = estimated discharge;

$Q_{SPI}$  = estimated discharge with SPI index;

$Q_m$  = measured discharge.

**Table 4.** Comparison between measured discharge ( $Q_m$ ), estimate discharge ( $Q_e$ ) and estimated discharge with SPI index ( $Q_{SPI}$ ).

September 2018				
$Q_m$	$Q_e$	$\varepsilon$	$Q_{SPI}$	$\varepsilon$
(l/s)	(l/s)	(%)	(l/s)	(%)
657.44	580.41	11.72	622.03	5.69

Results show that the proposed method could provide reliable results on karst spring discharge estimation using a rainfall-input model, especially referred to minimum values, which are the most important to be well forecasted, in provisional modelling, for an adequate water management. In particular, they show that it is possible to express the spring discharge as a linear combination of monthly rainfall values, properly multiplied by specific coefficients. Coefficients were obtained by cross correlation analyses and numerically define the incidence of previous monthly rainfall data on the spring flow value of the specific month considered

Due to the lack of spring flow rates monitoring in many areas of Italy, this kind of spring response modeling could become a useful tool for supporting Italian water agencies to face drought issues and planning a proper water resource management based on a quantitative knowledge of groundwater availability.

In particular, for Capodacqua di Spigno Spring, DICEA will intensify all monitoring activities in order to evaluate the method reliability and provide to the local water supply agency (Acqualatina S.p.A.) a hydrogeological model explaining, more in details, the behavior of the spring and its feeding aquifer.

**Author Contributions:** Conceptualization, G.S., F.M.D.F. and S.I.; methodology, F.M.D.F. and S.I.; formal analysis, F.M.D.F., S.I. and G.G.; data curation, F.M.D.F. and S.I.; writing—original draft preparation, G.S., F.M.D.F., S.I. and G.G.; visualization, F.M.D.F. and S.I.; supervision, G.S..

**Funding:** This research received no external funding.

**Acknowledgments:** Authors would like to thank Acqualatina S.p.A. for data availability and technical support.

**Conflicts of Interest:** “The authors declare no conflict of interest.”

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