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To cite this article: F. Cervi, G. Blöschl, A. Corsini, L. Borgatti & A. Montanari (2017) Perennial springs provide information to predict low flows in mountain basins, Hydrological Sciences Journal, 62:15, 2469-2481, DOI: [10.1080/02626667.2017.1393541](https://doi.org/10.1080/02626667.2017.1393541)

To link to this article: <https://doi.org/10.1080/02626667.2017.1393541>

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Perennial springs provide information to predict low flows in mountain basins

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ABSTRACT

A new method for estimating low flows in ungauged rivers from minimum discharge of perennial springs is proposed. This spring-based approach (SBA) is tested in 21 catchments from the northern Apennines, Italy. First, the hydrogeological behaviour of each geological formation and superficial deposit is related to the spatial distribution and discharge of perennial springs in a test area using a Bayesian approach, weight of evidence (WoE). Second, the observed river flow exceeded for 95% of the observation period is related to the type of geological formations outcropping within the catchment. Finally, the q₉₅ low flows are estimated from the WoE weights. The SBA performance is assessed by leave-one-out cross-validation and compared with the results of a multiple regression (MR) model that accounts for selected catchment characteristics, but no springs. The results show that the SBA outperforms MR. The better performance of the SBA may be related to its ability to capture bedrock characteristics, which are the main controls of low flows in the study area.

ARTICLE HISTORY

Received 20 April 2017
Accepted 17 September 2017

EDITOR

D. Kousoyiannis

ASSOCIATE EDITOR

A. Langousis

KEYWORDS

low flow; perennial springs; spatial analysis; northern Apennines

1 Introduction

Estimates of river low flows are needed for many purposes in water resources management and engineering, such as the fulfillment of minimum discharge requirements, the planning of water uses and the design of micro-hydropower plants (Smakhtin 2001, Gustard 2004, Pyrcz 2004). Low flows are usually quantified through the computation of the q₉₅ index, i.e. the specific discharge (in L s⁻¹ km⁻²) that is exceeded for 95% of the time (Gustard *et al.* 1987, 1992, Castiglioni *et al.* 2009, Vezza *et al.* 2010). In gauged basins q₉₅ can easily be calculated from multi-annual series of daily discharge data (Tallaksen and van Lanen 2004).

Laaha and Blöschl (2005, 2006a) pointed out that q₉₅ could be estimated even from relatively short time series. Based on an analysis of streamflow of Austrian basins they found that the biases between q₉₅ obtained from data series with observation periods between 5 and 20 years do not exceed 10%. A similar conclusion was reached by Castellarin *et al.* (2004).

In ungauged basins, q₉₅ can be indirectly estimated on the basis of regionalization procedures that account for the physiographical, geomorphological, climatic, land-use and vegetation characteristics of catchments,

usually using some sort of regression model (Holder 1985, Gustard *et al.* 1987, Smakhtin 2001, Flynn 2003, Demuth and Young 2004, Laaha and Blöschl 2006a, Vezza *et al.* 2010). To define the regression model (RM), one first needs to identify a geographical region where the model applies, the so-called “homogeneous region” (Smakhtin 2001, Laaha and Blöschl 2006a). Furthermore, catchment characteristics must be pre-processed to reduce their number in order to limit model complexity. The choice of the catchment characteristics (or descriptors) is usually carried out by testing the explanatory power of the variables or by using expert knowledge.

One crucial issue in estimating low flows with current multiple regression (MR) models is how to capture the hydrogeological behaviour of the catchment of interest, which requires information on geological formations and soils. These characteristics control the water storage in the catchment and groundwater flow routing, which lead to the formation of spring discharge and low flows in rivers. Several authors have pointed out that the most influential hydrogeological control is the type and position of the catchment bedrock (see, for example, Merz and Blöschl 2005, 2009a, 2009b). In addition, Oxtobee and

Novakowski (2003) pointed out the key role played by the number, width and persistence of fractures in the bedrock, as well as its inclination and the general shape of the involved geological units (Oxtobee and Novakowski 2002, Millares *et al.* 2009). The above studies suggest or imply that it may not suffice to gather information on the percentage rock type in a catchment. Rather, the fracture behaviour and the geometry of geological units within the catchment may deliver useful information for the estimation of low flows.

The present study is based on the idea that the behaviour of geological units and their fractures can be inferred through information on the distribution and regime of perennial springs. In fact, springs are originated by preferential flow along the bedrock of a catchment and its fractures, and therefore may deliver significant information on subsurface connectivity and catchment storage (Anderson *et al.* 1997, Onda *et al.* 2001, Uchida and Asano 2010). Therefore, we aim to exploit the hydrogeological characteristics of a catchment, represented by the spatial distribution and minimum discharges of perennial springs, to improve the regional estimation of q_{95} . The approach is tested against the traditional MR method, in which widely available descriptors are used. The results are discussed in order to better understand the additional information delivered by spring data.

2 Data

2.1 Study area

The study area extends over 4900 km² in the northern Apennines, Italy, and includes the catchments between the Baganza and the Reno rivers (Fig. 1). Elevations range from more than 2000 m a.s.l. at the southern boundary of the study area to approximately 70 m a.s.l., decreasing toward the northeast. The mean annual precipitation distribution (calculated over the last 30 years; Antolini *et al.* 2017) reflects the topography of the Apennines: it exceeds 2000 mm year⁻¹ near the main watershed divide and decreases to about 900 mm year⁻¹ in the hilly areas close to the Po River plain. In the uppermost part of the study area, cumulative annual snow cover can reach 2–3 m in winter. Potential evapotranspiration ranges from a few tens of mm per year up to 600–650 mm year⁻¹ in the lowlands, indicating that the aridity index (Salinas *et al.* 2013) ranges from about 0.05 to 0.72.

Runoff response to precipitation events is very rapid (in the order of a few hours) and is related to the

geomorphological and lithological characteristics of the catchment (Gumiero *et al.* 2009). In particular, silts, clays and marls outcrop extensively and do not favour the infiltration of precipitation but rather cause quick surface runoff. Precipitation distribution during the year is characterized by a marked minimum in the summer season. This is reflected in spring and river low flow in the same period (August, September and October).

Perennial springs are prevalently located in correspondence with flysch rocks (i.e. repetitive sequences of regular beds composed of limestone, sandstones and clay-shales) or in ancient glacial deposits, and have minimum discharges on the order of 10 L s⁻¹ or less (Canedoli 1994, Corsini *et al.* 2009, Gargini *et al.* 2014, Cervi *et al.* 2015). Some exceptions, i.e. high discharge springs, are found in outcrops of highly fractured calcarenites (Mulino delle Vene springs: 40 L s⁻¹; Cervi *et al.* 2014), or evaporitic rock masses (Poiano springs: several hundreds of L s⁻¹; Chiesi *et al.* 2010).

2.2 River discharge data

Daily river discharge data from 27 gauges at 15 watercourses located in the study area were provided by ARPA-EMR (2014). After a first review of the dataset, data from six gauges were considered unsuitable due to suspected unreliability of rating curves, remarkable urbanization of the basin and the presence of artificial reservoirs and/or diversions. The remaining 21 gauges (see Fig. 1) have continuous records of 7 years or more (2003–2014). A recent observation period was chosen in order to focus on the current climate and maximize the number of stations. It is worth noting that hydro-metric stations in the study area were limited in number and scattered in space until the year 2000, and data gaps occurred in the period 2001–2003 due to poor calibration of rating curves and problems with data loggers and data transmission devices. However, as found by Castellarin *et al.* (2004) and Laaha and Blöschl (2005, 2006a), the record length that is used herein allows a reliable estimation of q_{95} , with a relatively small bias. A summary of q_{95} river low flows and specific mean annual runoff (MAR) for the selected 21 gauges is given in Table 1.

2.3 Spring data

Information is available on the location and discharge of springs for a reduced test area (RTA) of 1600 km² located within the study area. The RTA is representative of the whole study area in terms of outcropping

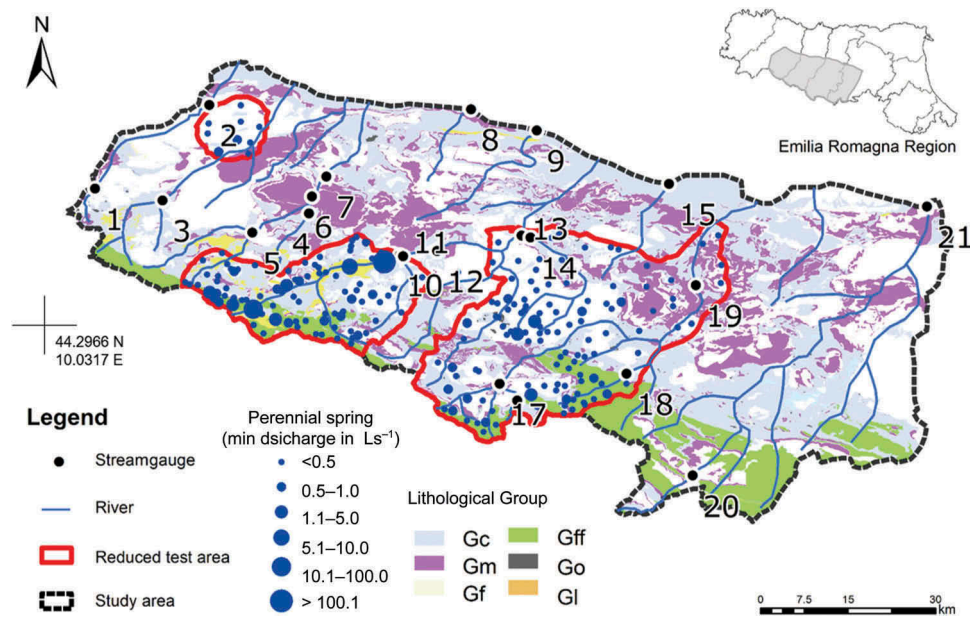


Figure 1. Total study area and the reduced test area. Selected streamgauges are numbered 1–21 (see Table 1 for description). Spring locations together with lithological groups of geological formations as suggested by Civita (2005) are also shown (see Section 2.4 for explanations).

Table 1. Streamgauges in the study region, along with their catchment areas (AREA), mean annual runoff (MAR) and low flows exceeded 95% of the time (q95).

Code	Name	AREA (km ²)	MAR (L s ⁻¹ km ⁻²)	q95 (L s ⁻¹ km ⁻²)	No. of years
1	Baganza Berceto	16	21.4	2.5	10
2	Baganza Marzolarà	129	16.6	3.3	11
3	Parma Corniglio	111	29.8	4.0	7
4	Lonza	62	9.8	0.2	8
5	Enza Selvanizza	85	5.4	2.8	7
6	Enza Vetto	299	12.2	3.0	9
7	Tassobbio Compiano	101	7.1	0.6	12
8	Crostolo Puianello	86	8.2	1.5	11
9	Tresinaro Ca de Caroli	150	12.9	0.7	9
10	Secchia Gatta	233	20.7	3.4	8
11	Secchiello Gatta	72	18.4	1.7	7
12	Secchia Cavola	348	20.6	3.0	11
13	Secchia Lugo	693	18.5	2.2	12
14	Rossenna	187	11.5	0.6	12
15	Tiepidò Gorzano	43	13.6	1.3	7
16	Acquicciola Fiumalbo	18	25.0	3.1	10
17	Scoltenna Pievepelago	140	16.8	5.9	12
18	Leo Fanano	38	13.6	5.1	11
19	Panaro Samone	584	18.8	4.1	12
20	Reno Pracchia	40	30.9	5.2	12
21	Reno Casalecchio	1056	13.8	1.0	11

bedrock and deposit formations (Fig. 1). A refined inventory of perennial springs based on field surveys was compiled for the test area. To this end, all the

available data on spring locations and their minimum discharge were collected from:

- institutions in charge of the management of water resources (river basin authorities, local administration and managers of water supply systems);
- unpublished reports and master's degree theses from the relevant universities;
- master plans of the local administration of the cities of Modena and Reggio Emilia and the Emilia-Romagna region (Servizio Geologico, Sismico e dei Suoli of Regione Emilia-Romagna, 2016a).

The result of these activities is an extensive and original spring dataset. From these data, a “spring point” (SP) is defined as a unit spring with a discharge of 0.1 L s⁻¹. For example, a spring with a minimum discharge of 1 L s⁻¹ is represented in the dataset by 10 SP. The resulting database contains a total of 11 770 SP, which are used as supporting evidence for the spatial modelling (see Section 3.1). The representation in terms of SP allows one to obtain a comprehensive description of the spatial distribution of emerging springs and their flow as an indicator of the magnitudes and abundance of fractures in the bedrock connected to the rock water table.

Table 2. Catchment descriptors included in the regional regression analysis.

Acronym	Variable	Units	Minimum	Mean	Maximum
A	Catchment area	km ²	18	229	1056
H^0	Altitude of streamgauge	m	60	372	1085
H^+	Maximum altitude	m	738	1755	2170
H_R	Range of altitude	m	612	1383	1953
H_M	Mean altitude	m	388	876	1463
S_M	Mean slope	(-)	14.4	18.4	24.2
S_{SL}	Slight slope	(-)	1.4	5.4	12.1
S_{MO}	Moderate slope	(-)	35.3	57.6	73.5
S_{ST}	Steep slope	(-)	19.4	37.0	62.7
$P - PET$	Precipitation – potential evapotranspiration	mm	223	592	1097
G_C	Clay	%	7.6	28.4	41.8
G_M	Marl	%	0.7	5.8	16.4
G_F	Flysch	%	16.7	45.4	74.1
G_{FF}	Foreland flysch	%	0	10.2	41.1
G_O	Ophiolites	%	0	0.1	1.1
G_L	Limestone	%	0	4.2	15.3
D_{560}	Stream network density	m	km ⁻²	380	490
L_F	Forest	%	14.2	45.6	70.6
L_G	Grassland	%	6.5	14.9	30.4
L_A	Agriculture	%	10.4	31.8	63.2

2.4 Catchment data

Following Laaha and Blöschl (2006b) in applying the MR approach, 20 catchment characteristics (or descriptors) related to area (A), topographic height (H), topographic slope (S), precipitation (P), geology (G), land use (L) and stream network density (D) are used. A summary of descriptors is given in Table 2. The percentage values represent the area covered by a class relative to the catchment area. The database of the Emilia-Romagna administrative region (Servizio Geologico, Sismico e dei Suoli 2016b) was used to collect information on geological formations and superficial deposits at the 1:10 000 scale. The database contains 125 different bedrock formations and 30 classes of superficial deposits. Land-use descriptors (L_F , L_G , L_A , see Table 2) are derived from a 1:50 000-scale survey carried out in 2005 by Servizio Geologico, Sismico e dei Suoli of the Emilia-Romagna region.

The descriptors related to geology (G_C , G_M , G_F , G_{FF} , G_O , G_L , see Table 2) are obtained by grouping into six classes the 125 geological formations included within the geological database (Fig. 1). This simplification is required in order to take into account the main hydrogeological features of the area, i.e. by considering the permeability and storativity of the formations related to their lithological characteristic, as suggested by Civita (2005).

Furthermore, average annual precipitation (P) and potential evapotranspiration (PET; Thornthwaite and Mather 1957) are calculated for the corresponding

reference period (maximum time window: 2003–2014) for 42 stations (see Supplementary material, Table S1; data available in ARPA-EMR, 2014). The average values for catchments are estimated by spatial interpolation via ordinary kriging (Isaaks and Srivastava 1989).

Area (A), topographic slope (S_M , S_L , S_{MO} , S_{ST}), topographic height (H_0 , H^+ , H_R , H_M) and stream network density (D) are derived from a 5×5 m gridded digital terrain model that has been created by digitalization and linear interpolation of contour lines represented in the regional topography map at a scale of 1:5000. In more detail, slight slope (S_{SL}), moderate slope (S_{MO}) and steep slope (S_{ST}) are derived by using natural break classifications (a method that minimizes the average deviation of each class from the class mean, while maximizing its deviation from the means of the other groups; see Jenks 1967 for further details).

3 Methods

3.1 Spring-based approach

The spring-based approach (SBA), is based on the following assumptions:

- The low-flow discharge of the streams draining a basin is related to the type of geological units and superficial deposits outcropping in the basin (Armbruster 1976, Institute of Hydrology 1980, Musiaki *et al.* 1984, Bingham 1986, Aucott *et al.* 1987, Gustard *et al.* 1987, Rogers and Armbruster 1990, Pyrcce 2004, Schneider *et al.* 2007). Such an assumption is justified by considering that stream discharge during recession periods is driven mostly by groundwater flow, which is relevant where bedrock and superficial deposits have high storativity. The infiltrated water emerges in perennial springs which are the main sources of stream water during dry periods.
- The spatial distribution of perennial springs and their minimum discharge is a proxy for the permeability and storativity of hydrogeological complexes. Therefore, it is in turn related to river low flows.

The second assumption implies that storativity is related to the probability of observing SP conditioned to the underlying geological unit and superficial deposit (Corsini *et al.* 2009, Ozdemir 2011, Naghibi *et al.* 2016). The SP probability conditioned to the underlying geological unit and superficial deposit is

estimated by the weight of evidence (WoE) method (Bonham-Carter *et al.* 1989, Bonham-Carter 2002), using the software packages Arc-SDM Spatial Data Modeller Extension implemented in a GIS platform (Kemp *et al.* 2001). The WoE method was originally developed for a non-spatial application in medicine, where the evidence consisted of a set of symptoms and the hypothesis was that the patient is affected by a given disease. For each symptom, a pair of weights was calculated, for presence and absence of the symptom. The values of the weights depended on the measured association between the symptom and the pattern of disease in a large group of patients. The weights could then be used to estimate the probability that a new patient would get the disease, based on the presence or absence of symptoms.

The WoE method was subsequently adapted to mineral potential mapping (Bonham-Carter *et al.* 1989, Agterberg 1992, Asadi and Hale 2001). In this case, the evidence consists of a set of exploration datasets (maps), and the hypothesis is that the location has a mineral potential. Weights are estimated from the measured association between known mineral occurrences and the values on the maps to be used as predictors.

In the present study, we use the WoE method to associate the presence of SPs with the type of geology and superficial deposits. To apply the WoE method, one needs to define the probability $P(\text{SP})$ of finding a spring point in the RTA. To this end, we discretized the RTA into pixels of 10×10 m and located the pixels where SPs were present. When a number, $k > 1$, of SPs are present in a pixel, we assume that k pixels at the same location are occupied by a SP. Then, the probability $P(\text{SP})$ is given by:

$$P(\text{SP}) = \frac{N(\text{SP})}{N(\text{RTA})} \quad (1)$$

where $N(\text{SP})$ and $N(\text{RTA})$ are the number of pixels occupied by SPs and the total number of pixels in the RTA, respectively.

Next we considered the $n = 125$ classes of geological formations G_i (with $i = 1, 2, \dots, n$) and $m = 30$ types of superficial deposits SD_j (with $j = 1, 2, \dots, m$). The prior probability of finding class G_i within the RTA (i.e. $P(G_i)$) is:

$$P(G_i) = \frac{N(G_i)}{N(\text{RTA})} \quad (2)$$

where $N(G_i)$ is the number of pixels occupied by G_i in the RTA. Finally, the conditional probability of the outcome G_i given SP, $P(G_i|\text{SP})$, is estimated as:

$$P(G_i|\text{SP}) = \frac{N(\text{SP} \cap G_i)}{N(\text{SP})} \quad (3)$$

where $N(\text{SP} \cap G_i)$ indicates the number of pixels where one can find both SP and G_i in the RTA.

From the above probabilities, the weights $W_{G_i}^+$ for each class of geological formations G_i are calculated as:

$$W_{G_i}^+ = \ln \frac{P(G_i|\text{SP})}{P(G_i)} \quad (4)$$

According to Equation (4), a value of $W_{G_i}^+ > 0$ means the conditional probability $P(G_i|\text{SP})$ is higher than the prior probability $P(G_i)$, i.e. there is a higher probability of finding the geological formation G_i when SPs are present. The higher the value of $W_{G_i}^+$, the greater the dependence of G_i on springs.

In contrast, $W_{G_i}^+ < 0$ indicates a negative dependence between the supporting evidence SP and class (G_i). If the conditional probability $P(G_i|\text{SP})$ is equal to the prior probability $P(G_i)$, SP and G_i are uncorrelated and $W_{G_i}^+ = 0$. By substituting G_i with SD_j in Equations (1)–(4), the corresponding $W_{\text{SD}_j}^+$ values for superficial deposits obtained and the above considerations on positive and negative dependence are still valid. Weights $W_{G_i+\text{SD}_j}^+$ are estimated analogously by referring to each possible combination of G_i and SD_j . The conditional independence between geological formations and soil deposits is checked by the χ^2 test (Agterberg and Cheng 2002), as required by the WoE method to avoid overestimating the final weight ($W_{G_i+\text{SD}_j}^+$).

In order to select which of the three different input datasets of causal factors $W_{G_i}^+$, $W_{\text{SD}_j}^+$ and $W_{G_i+\text{SD}_j}^+$ provides the best performance, success rate curves are used (Chung and Fabbri 1999, Van Westen *et al.* 2003). These are graphs showing on the x - and y -axes, respectively, the percentage of cumulated study area with progressively lower weight values and the cumulative percentage of correctly predicted SP for a specific weight value. The larger the percentage of SP in the smallest cumulated area of higher weight values, the better the model. The 1:1 line in the graph indicates a random distribution of the supporting evidence, which implies independence between SP and the causal factors. In our case, this would imply that the information delivered by springs is not useful for predicting low flows.

In the case where the best performing information is that delivered by geological formation G_i , only the weights $W_{G_i}^+$ have to be used to predict low flows for the whole study area (4900 km²) and then be combined

Table 3. Weighted mean W_c^+ value for each gauged basin estimated by Equation (5).

Code	q95 ($L s^{-1} km^{-2}$)	W_c^+
1	2.5	-0.85
2	3.3	-0.31
3	4.0	-0.45
4	0.2	-1.37
5	2.8	-0.53
6	3.0	-0.77
7	0.6	-1.24
8	1.5	-1.24
9	0.7	-1.31
10	3.4	-0.34
11	1.7	-0.87
12	3.0	-0.61
13	2.2	-0.52
14	0.6	-1.10
15	1.3	-1.29
16	3.1	-0.18
17	5.9	-0.03
18	5.1	-0.11
19	4.1	-0.31
20	5.2	0.09
21	1.0	-1.01

with the catchment boundaries to obtain the weighted mean of the W_{Gi}^+ in each catchment, W_c^+ , as:

$$W_c^+ = \frac{\sum_{i=1}^m W_{Gi}^+ \cdot A_{Gi}}{A_c} \quad (5)$$

where $i = 1, 2, \dots$, A_{Gi} is the area of each geological formation within the catchment boundary and A_c is the catchment area.

A linear regression is subsequently established between the independent variable W_c^+ and the dependent variable q95 for the 21 gauged basins (see Table 3). A sketch of the SBA workflow is presented in Figure 2. The regression model can then be used to predict q95 in ungauged basins.

3.2 Multiple regression model

According to previous studies (Pyrce 2004, Laaha and Blöschl 2005, 2006a, 2006b, Vezza *et al.* 2010), q95 can also be estimated by a MR model with j catchment characteristics as independent variables. The MR model can be written as:

$$y = c_0 + c_1x_1 + c_2x_2 + \dots + c_kx_k + \varepsilon \quad (6)$$

where y is the estimate of the considered low-flow index (in this case q95), x_k and c_k ($k = 1, 2, \dots, j$) are the catchment characteristics and the regression model coefficients, respectively; and ε is the residual error of the model, which is assumed to be independent of x_k .

The method needs *a priori* selection of the most important independent variables, which have been chosen using a stepwise regression approach. Accordingly, variables are added one by one to the model and the F

statistic (ratio between the mean regression and error sums of the square) has to be significant at a selected level (0.05). After each variable is added to the model, the stepwise method assesses all of the variables already included in the model and deletes any variable that does not produce an F statistic significant at the selected confidence level (Davis 2001).

3.3 Analysis of predictive performance

The performance of the SBA and MR models is tested by leave-one-out cross-validation (Efron and Tibshirani 1993). The cross-validation procedure is carried out by using the non-supervised frequency analysis tool implemented in the R statistical package (R Core Team 2016), which follows these consecutive steps:

- (1) in turn, one of the $c = 21$ catchments, called b , is removed from the dataset simulating ungauged conditions for basin b ;
- (2) the methods are calibrated using all catchments excluding b ;
- (3) the methods are applied to predict q95 specific discharge for basin b ;
- (4) steps 1–3 are repeated for each of the other $c - 1$ catchments;
- (5) the prediction error for each catchment is estimated and the error statistics are analysed.

The same approach was used by Viglione *et al.* (2013).

According to Laaha and Blöschl (2006b), the cross-validation prediction error V_{cv} can be estimated as:

$$V_{cv} = \frac{1}{c} \sum (q'95_b - q95_b)^2 \quad (7)$$

where $q95_b$ is the observed q95 specific discharge for catchment b and $q'95_b$ is the model prediction in cross-validation mode, i.e. without using observed low flows of catchment b . The root mean square error (RMSE) based on cross-validation is therefore:

$$RMSE_{cv} = \sqrt{V_{cv}} \quad (8)$$

and the coefficient of determination based on cross-validation, R_{cv}^2 , is:

$$R_{cv}^2 = \frac{(V_q - V_{cv})}{V_q} \quad (9)$$

where V_q is the spatial variance of the observed specific low-flow discharge, q95. Together with $RMSE_{cv}$ and R_{cv}^2 , goodness-of-fit statistics are provided through the

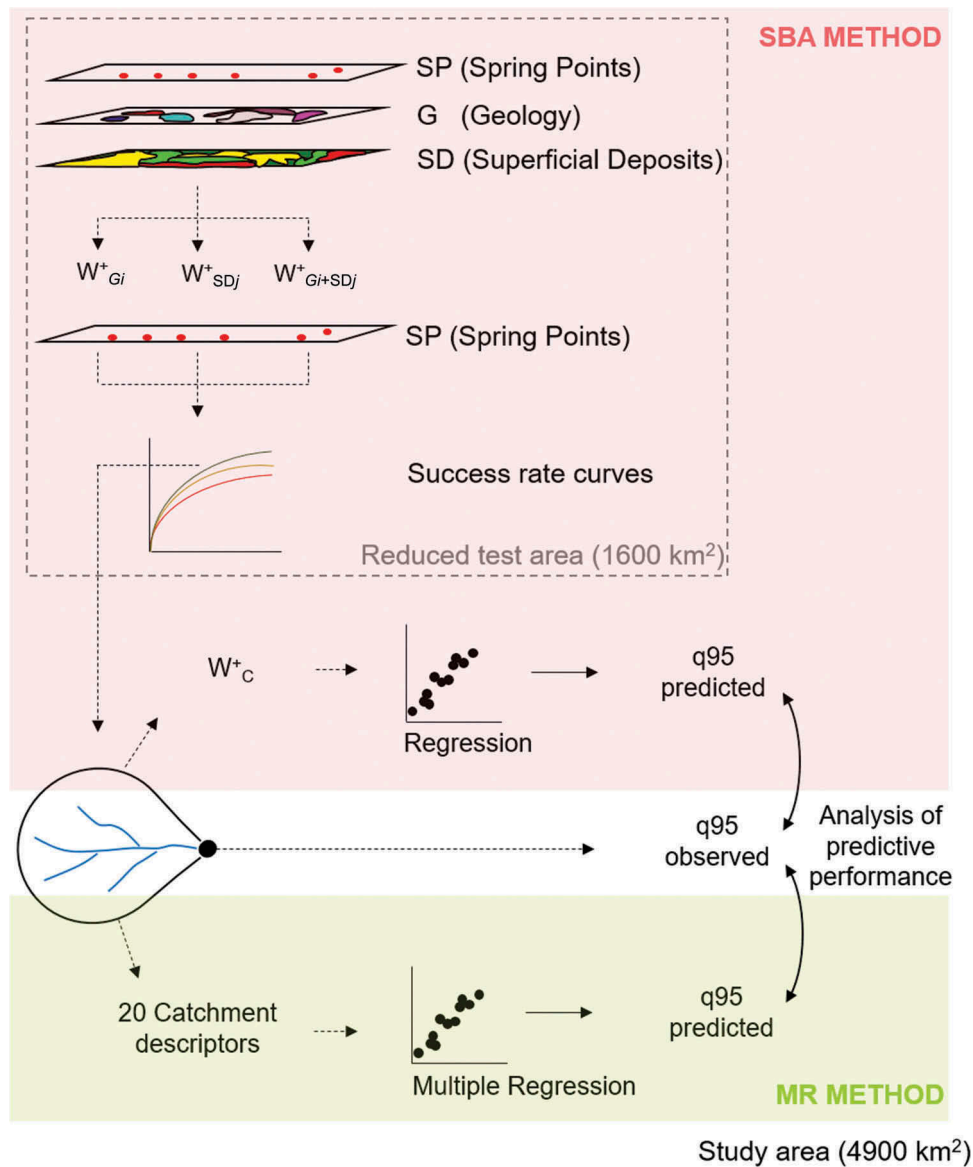


Figure 2. Methodological approach followed. The upper (red) shaded part indicates the proposed spring-based approach (SBA method), while the lower (green) shaded part indicates the alternative multiple regression (MR) method.

adjusted coefficient of determination R^2_{adj} . Finally, the average absolute normalized error (ANE) is estimated as:

$$\text{ANE} = \frac{1}{c} \sum \left| \frac{q'95_b - q95_b}{q95_b} \right| \quad (10)$$

4 Results

4.1 Calibration of the spring-based approach

The SBA is tested by combining two different input datasets of causal factors (geological formations and superficial deposits) and a combination of both. Geological formations and superficial deposits are classified into $n = 125$ formations with areas ranging from

0.0009 to 160.3 km², and $m = 30$ deposits with areas ranging from 0.006 to 885.2 km². The performances of the three different methods are shown in Figure 3.

It can be seen that the use of W^+_{SDj} produces a success rate curve that is close to the 1:1 line, so that an approximately random distribution of SPs with reference to the causal factor “surface deposits” can be ascertained. This is further confirmed if W^+_{Gi+SDj} is considered. In fact, the use of both causal factors does not significantly improve the success rate of the model over the test that considers geological formations only (W^+_{Gi} ; see Supplementary material, Table S2). This indicates that, for the study area, the geology of the bedrock is the main causal factor for the occurrence of the SPs (Fig. 3), and therefore only W^+_{Gi}

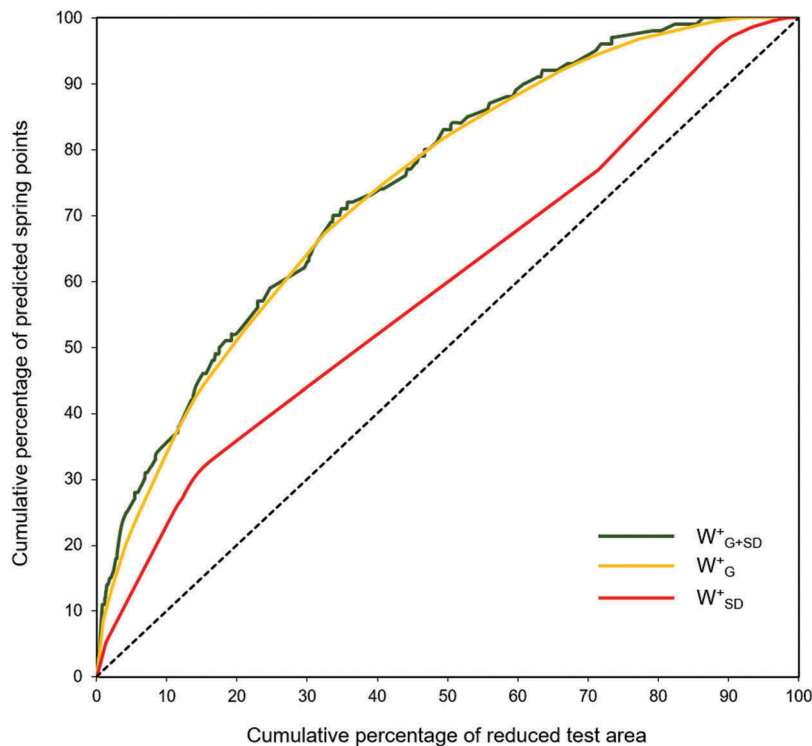


Figure 3. Success rate curves of the three causal factors in the SBA used as evidence: W^+_{SD} , W^+_G , W^+_{G+SD} , which refer to superficial deposits, geological formations and a combination of both, respectively. The 1:1 line (dashed black line) represents no statistical relationship between spring points (SP) and the causal factors.

should be used to obtain the weighted mean W^+_C for each catchment (by means of Equation (5)).

Table 3 reports the weighted mean W^+_C value for each gauged basin and the related q95 discharge. The coefficient of determination (R^2) obtained from the linear regression (see Section 3.1) is 0.86, which indicates a satisfactory predictive performance.

4.2 Calibration of the multiple regression approach

Catchment characteristics related to topographic elevation (H), stream network density (D) and precipitation (P) were scaled by an integer power of 10 to give similar magnitude, in order to avoid sensitivity of the analyses to different scales of the descriptors. As suggested in Section 3.3, the independent variables were selected by a stepwise regression approach. In the end, only the maximum altitude (H^+ , in 10^2 m), range of altitude (H_R , in 10^2 m), difference between precipitation and potential evapotranspiration ($P - PET$, in 10^2 mm) and moderate slope (S_{MO} , dimensionless) were included within the model. The resulting MR model, with $q95$ in $L s^{-1} km^{-2}$, is given by:

$$q95 = 7.10 - 0.18H^+ + 0.16H_R + 0.38(P - PET) - 0.10S_{MO}$$

with a coefficient of determination R^2_{adj} of 0.70.

4.3 Comparison between methods

The SBA and MR methods were finally compared using a leave-one-out cross-validation of the regression estimates: scatter plots of observed *vs* (a) predicted values and (b) cross-validation plots are reported in Figure 4. Table 4 shows the regressions obtained for each model class, along with R^2_{adj} , $RMSE_{cv}$ and the cross-validation coefficient of determination R^2_{cv} . The $RMSE_{cv}$ and R^2_{cv} provide a useful overview of the prediction reliability as they are obtained from cross-validated residuals. The results indicate that the SBA method performs better, with a coefficient of determination of $q95 = 79\%$, against 61% for the regional regression approach.

5 Discussion

The comparison of the spring-based approach (SBA) and the multiple regression (MR) approach in the study region in the Apennines suggests that the former

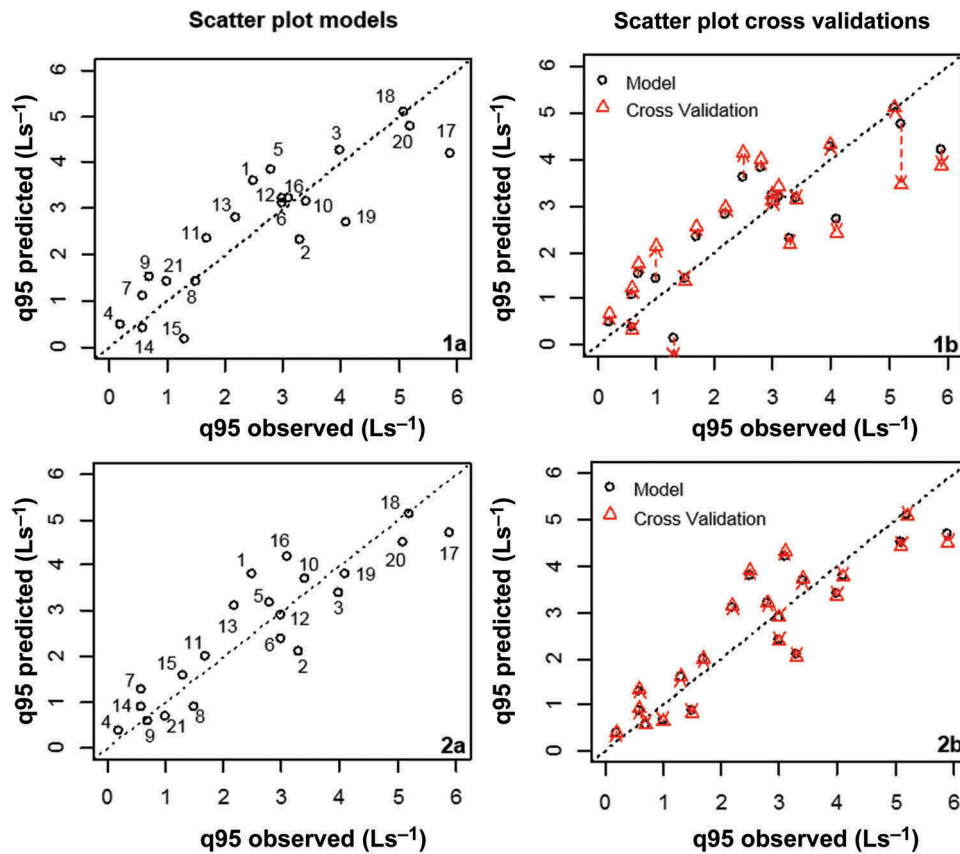


Figure 4. Observed and estimated specific low-flow discharge (q95) of 21 gauged basins (with catchment code) and cross-validation scatter plot: multiple regression method (top) and spring-based approach (bottom).

Table 4. Performance indicators for the SBA and MR method estimated q95 low flows in ungauged basins.

Method	R^2_{adj}	RMSE _{cv}	R^2_{cv}	ANE
SBA	0.82	0.73	0.79	0.33
MR	0.70	0.98	0.61	0.39

outperforms the latter in estimating q95 river low flows. The adjusted coefficient of determination R^2_{adj} (based on specific q95 discharges) is 0.82 and 0.70, respectively, for SBA and MR. The regression model performance is similar to typical values found in the literature. The meta-analysis of Salinas *et al.* (2013, their Fig. 3) summarized 11 studies that used global regression, with an average performance of $R^2 = 0.65$, and seven studies that used regional regression (where the domain was divided into sub-regions), with an average performance of $R^2 = 0.75$. The SBA method proposed here performs better than these typical values. The average absolute normalized errors (ANE) obtained (0.33 and 0.39 for the SBA and MR methods, respectively) are also consistent with values in the literature. Based on an analysis of 1895 catchments, Salinas *et al.* (2013, their Fig. 5) obtained ANE = 0.40 and ANE = 0.30 for global and regional regressions, respectively, in climate conditions consistent with an aridity

index equal to 0.5. In addition, the lower value of ANE (0.33) in the case of SBA further confirms that the performance is slightly higher than that of MR (ANE = 0.39).

The MR approach is the most common method for estimating low-flow indices (such as q95) in ungauged basins. It is based on the use of a linear relationship linking q95 to all the processes driving low flows, summarized by selected physiographical, geomorphological, climatic and land-use descriptors. Global multiple regression models are not usually fully representative of low-flow processes over large domains. As suggested by several authors (Castellarin *et al.* 2004, Laaha and Blöschl 2006a, Vezza *et al.* 2010), improved results can be obtained by splitting the study domain into several homogeneous regions of approximately uniform low-flow behaviour in which region-specific linear regressions can be established. Homogeneous regions can be defined using various statistical techniques by analysing either river discharge data (seasonality indices; Merz *et al.* 1999) or both discharge and catchment descriptors (classification and regression trees algorithm: Laaha 2002; weighted cluster analysis: Nathan and McMahon 1990; and residual pattern approach: Hayes 1992).

Although regression approaches applied to homogeneous regions usually outperform the global regressions carried out on larger domains (Salinas *et al.* 2013), splitting into homogeneous regions does not always allow better modelling of the physical processes affecting low flows, as the superior performance may be due to improved fitting of the linear regressions applied to a restricted sample with less variability. A side effect is that the descriptive capability of each explanatory variable may vary from region to region (Veza *et al.* 2010). Therefore, the selection of the catchment descriptors requires careful *a priori* selection for each homogeneous region.

Among the different descriptors in q95 estimates, the bedrock behaviour surely plays an important role, as during the low-flow period streams are fed by groundwater flow from within the bedrock itself. In order to take bedrock effects into account, MR models have been built, using as geological independent variables, simplified geological indices from the analysis of geological formations and superficial deposits, which are based respectively on lithological and textural features (Gustard *et al.* 1992, Nathan and McMahon 1992, Castellarin *et al.* 2004, Laaha, and Blöschl 2006a). Such data have allowed these descriptors to be grouped into a few classes to represent permeability and storativity characterizing each unit, as shown, for example, in the MR analysis presented herein (see Section 2.4 and Table 2).

The SBA uses a new type of information that may overcome the above drawbacks of the MR approach. The location and minimum flow of perennial springs have been used here to assess the permeability and storage of the bedrock, which are considered important controls of river low flows. The results obtained by the WoE analysis confirm that the behaviour of superficial deposits does not explain well the presence and minimum flows of springs. This finding may be related to the clay-rich texture and high permeability of the deposits, such as torrent fans, scree slopes, rock block slides and rock falls. Also, these deposits have limited extent in the study area. In contrast, the geological formations turned out to be clearly related to the position and flow of springs.

To shed more light on the role of geological formations, Table 5 presents the mean and standard deviation of the weights W^+_{Gi} obtained from the analysis of

the statistical relationships between SP and geological formations themselves. The latter have been grouped as for the MR approach (see Section 2.4 and Table 2). As expected, the WoE analysis confirms that clay and marl indicate reduced probability of the presence of springs (for G_C and G_M , the mean of the corresponding W^+_{Gi} is -0.94 and -0.79 , respectively). Conversely, limestone is associated with high probability of springs (for G_L , mean W^+_{Gi} is 1.02). This is consistent with the high standard deviations of W^+_{Gi} of the clay and marl descriptors (± 0.73 and ± 0.51 , respectively), and the low values for limestone (± 0.05). This finding is explained by the fact that, in the study area, the majority of the springs originate from the contact between high permeable units such as G_C and G_M (above) and low permeable ones (below). Therefore, springs are located along boundary lines separating different geological formations, and perhaps erroneously allocated, thus causing a higher dispersion of the related W^+_{Gi} values.

The results also suggest that the foreland flysch group (G_{FF} ; i.e. flysch formations that are mainly composed of sandstones beds) is more correlated to springs than flysch (for G_{FF} and G_F , W^+_{Gi} is 0.21 and 0.08 , respectively). Therefore, clustering all flysch formations into the same class seems not to be appropriate. In fact, flysches can behave alternatively as aquicludes (negative W^+_{Gi}), aquitards or aquifers (positive W^+_{Gi}), depending on the thickness of the clayey beds, their structural characteristics and their response to tectonic stresses in terms of fracturing (Gargini *et al.* 2008, Petrella and Celico 2009, Vincenzi *et al.* 2009, Bense *et al.* 2013).

By considering the possible influence of these results on q95 estimates in ungauged basins, the inappropriateness of grouping geological formations by their lithological characteristics as the only criteria clearly emerges in the presence of flysches. Given that the latter formations outcrop in several mountain chains, this indication is particularly relevant. This finding is further confirmed by the performance of the MR model, in which geological descriptors are not included as they turn out to be poorly descriptive, and the most important variable is found to be precipitation depurated by potential evapotranspiration ($P - PET$). These

Table 5. Mean and standard deviation (SD) of the weights W^+_{Gi} for groups of geological formations as reported in Table 2.

Geological formation groups in MR	Mean of W^+_{Gi}	SD of W^+_{Gi}
Clay, G_C	-0.94	± 0.73
Marl, G_M	-0.79	± 0.51
Flysch, G_F	0.08	± 0.61
Foreland flysch, G_{FF}	0.21	± 0.19
Ophiolites, G_O	0.35	± 0.01
Limestone, G_L	1.02	± 0.05

results are substantially in agreement with those reported in Vezza *et al.* (2010; their Fig. 4 and Table 4), for a homogeneous region in the vicinity of our study area (i.e. the Apennine-Mediterranean area of the Piemonte region), in which the maximum altitude (implying higher orographic precipitation and lower evapotranspiration) of the catchments is the only relevant descriptor for low-flow estimates.

It should be pointed out that the descriptor $P - PET$ may already be implicitly considered by the WoE analysis, as springs are influenced by the precipitation distribution. For instance, an equal extension of the i th geological formation (i.e. characterized by the same values of storativity and permeability) outcropping close to the main watershed divide may result in a larger number of SPs than along the foothills of the northern Apennines, because of the different magnitudes of mean precipitation, which in turn lead to higher values of minimum discharge.

Although the SBA was shown to outperform the more common MR method, the SBA does require a large amount of data (in particular minimum discharges of springs), which may be difficult to obtain. Moreover, further efforts should be directed towards accounting for additional causal factors, such as fault zones, that can enhance the aquifer-like behaviour of geological formations. In fact, Corsini *et al.* (2009), referring to a small area (68 km²) in the northern Apennines, demonstrated the effectiveness of the WoE method to statistically rank the effect of these geological features on groundwater flow paths. In particular, they found a higher probability of springs up to 60 m away from the faults. There is therefore potential to further develop the SBA method proposed in this paper.

6 Conclusions

We present a novel approach for estimating river low flows by taking advantage of the information contained in the spatial distribution of perennial springs and their minimum discharges. The approach, termed SBA, relates the location of groundwater springs to bedrock formations and superficial deposits through the weight of evidence method. It is found that, for this specific study area in the northern Apennines, distribution and discharge of perennial springs depend on the bedrock formations rather than superficial deposits. This allows the aquifer-like behaviour of each geological formation to be assessed through information on springs and then used to predict low flows.

Comparisons of estimated and observed low river flows in a cross-validation mode indicate that the SBA explains the spatial distribution of the low-flow index q_{95} better than the traditional regression approach. It can therefore

be concluded that the use of the location of perennial springs together with their minimum discharge is useful for estimating low flows in ungauged basins, as the additional information springs deliver about the aquifer-like behaviour of the bedrock may much better characterize the subsurface flow system than the traditional regression method based on available catchment attributes.

Future efforts should focus on accounting for the spatial distribution of faults in the bedrock within the SBA method. When available, this additional information is expected to deliver additional predictive power to the approach.

Acknowledgements

The authors would like to thank A. Viglione for the helpful advice during the set-up of the cross-validation technique. Comments by A. Langousis, B. Schaeffli and an anonymous reviewer allowed the earlier version of the manuscript to be significantly improved.

Disclosure statement

No potential conflict of interest was reported by the authors.

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