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Low Flows Regionalization in North-Western Italy

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Abstract Prediction of low flows in ungauged catchments is needed in many branches of water resources management, including water availability and river ecology studies. In this paper we analyze the regional variability of q_{95}, i.e., the specific discharge that is exceeded 95% of the time, in North-Western Italy (Piemonte and Valle d'Aosta Regions). Multiple regressions with morphoclimatic catchment characteristics are applied in subregions obtained through four classification methods: Seasonality Indices (SI), Classification and Regression Trees (CRT), Residual Pattern Approach (RPA) and Weighted Cluster Analysis (WCA). All the classification methods separate the South-Eastern Apennine-Mediterranean area from the rest of the study domain (the Alps mountain range), even if they use different criteria to carry out this division (e.g., the percentage of forest, seasonality of low flows, combination of several parameters). In the Apennine-Mediterranean part of the area, low flows occur in summer with a long period of drought and are mainly due to dry climate, moderate snowpack storage and high evapotranspiration. In Alpine catchments low flows occur in winter and vary according to precipitation, elevation, interactions with aquifers and land cover. Within the Alpine mountain range the CRT algorithm identifies a number of small high-elevation catchments in which the intense drought period during winter has the soil freezing processes as the driving force. From a statistical point of view, the CRT model outperforms the

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models obtained by the other classification techniques in terms of explained variance (69%). Because of this, and given the meaningful hydrological interpretation of the results, we use the CRT model for the regionalization of q_{95} in Piemonte and Valle d'Aosta. Lastly, as operational procedure for future low flow regionalization studies, we suggest that more classification methods should be applied to assist the critical analysis of the results.

Keywords Low flows · Regionalization · Regional regression · Classification and regression tree · CART

1 Introduction

Low flow is a seasonal phenomenon and an integral component of the flow regime, normally due to groundwater discharge or surface discharge from lakes, marshes, or melting glaciers. According to the World Meteorological Organization, a possible definition of low flow is 'the flow of water in a stream during prolonged dry weather' (WMO 1974). The ability to estimate low flows magnitude and frequency in river streams is an important issue for water-supply planning, reservoir storage design, maintenance of quantity and quality of water for irrigation, recreation and environmental flow requirements for wildlife conservation. In a regional-scale context, it is necessary to provide spatially distributed estimates of low flow, i.e., not only in monitored streams but also in ungauged watersheds. The study presented here is preparatory to a regional water planning in Piemonte Region (Noth-Western Italy) to evaluate the ecological discharges which will have to be released from existing and new water abstractions.

Smakhtin (2001) and Demuth and Young (2004) give an extensive list of possible approaches and techniques for low-flows estimation in ungauged catchments, which include regional regression, spatial interpolation, construction of regional curves and time series simulations. It is interesting to note that regional studies concerning low flows are developed also between countries in Europe, breaking the national boundaries. These activities are mostly associated with the FRIEND project (Flow Regimes from International Experimental and Network Data, e.g. FREND 1989; FRIEND 1994, 2006). In FREND (1989) 13 European countries were involved and the study of the low-flow regimes was carried out on 1350 rivers of NW Europe (Gustard and Gross 1989). FRIEND activities developed horizontally involving firstly the former Eastern European countries, rapidly expanded into the other parts of the world and having today over 100 countries involved within eight regional FRIEND groups. Examples of regional studies on low flows regarding Eastern and Central Europe are presented in FRIEND (1994) (see e.g. Kupczyk et al. 1994 and Kobold and Brilly 1994). Kupczyk et al. (1994) reported a study of low-flows regimes of Polish rivers, defining regional recession curves based on summer low flows, while Kobold and Brilly (1994) analyzed the relationship between different low flows durations at regional scale by using the mean annual ten day minimum as a key variable.

Considering possible approaches for low flows estimation in ungauged catchments, the regional regression approach, which correlates low flows indices and catchment characteristics, is the most widely used method (e.g. Kottegoda and Rosso

(2004) or see Smakhtin (2001) for a review of low-flow hydrology). Meaningful morphoclimatic descriptors of river basins have direct connection to the hydrological processes taking place in drainage basins. Ideally, these indices should play a role in the average water balance within the basin, with the morphologic ones related to the hydrologic response, and the climatic ones related to the water input.

If the study domain is large or very heterogenous in terms of low flows processes, a number of authors suggest to split the domain into sub-regions in which the low flow behavior is assumed to be homogeneous (e.g. Gustard et al. 1992; Vogel and Kroll 1992; Schreiber and Demuth 1997; Engeland and Hisdal 2009). The formation of these regions is performed by grouping the gauged sites according to a classification criterion using low flows data and/or catchments characteristics. Once catchments are classified into groups, the regional regression approach is applied to each subregion obtained and the performance of prediction models is checked by cross-validation.

Recently Laaha and Blöschl (2006a) investigated the performance of four catchment grouping strategies to estimate low flows indices in Austria by means of linear regressions within the subregions. The four methods are Residual Pattern Approach (RPA), Weighted Cluster Analysis (WCA), Classification and Regression Trees algorithm (CRT) and Seasonality Indices (SI). In the first technique (RPA), residuals from an initial global regression model are plotted in the geographic space and contiguous regions are manually obtained from the map looking at the patterns of these residuals. When contiguous regions are delineated, ungauged sites are allocated to the regions by their geographical location. In the context of low flow regionalization, the Weighted Cluster Analysis (WCA) was proposed by Nathan and McMahon (1990), who used 184 catchments in South-West Australia. The method is based on a number of different cluster analysis approaches and uses Andrews curves (Andrews 1972) for visualizing similarity in catchment characteristics within the groups. The Classification and Regression Trees approach (CRT) was used for the first time in low flows regionalization in Laaha and Blöschl (2006a). The approach (Breiman et al. 1984) divides a heterogeneous domain into a number of more homogeneous regions by an optimization technique. Laaha and Blöschl (2006a) also used a seasonality approach (SI) for classification that performs better than the others and allows to explain 70% of the spatial variance of q_{95} in Austria. The potential of this approach is likely related to the striking differences in seasonal low flow processes between catchments (Laaha and Blöschl 2006a) and was used, along with low flow estimates from short stream flow records (Laaha and Blöschl 2005), in the national low flow estimation procedure for Austria (Laaha and Blöschl 2007). Recently, Engeland and Hisdal (2009) and Kohnová et al. (2009) applied the same method of classification based on seasonality in Norway and Slovakia respectively.

In this paper we analyze and interpret the results of the four classification methods for low flow regionalization proposed by Laaha and Blöschl (2006a) in a different territorial context. Compared to Laaha and Blöschl (2006a) and Engeland and Hisdal (2009), we use a more comprehensive multiregressive approach on different transformations of the dependent variable (q_{95}) and the optimal classification is chosen based on both statistical performance and hydrological interpretation of the model parameters. Hereafter, in Section 2, we describe the study area, the streamflow data and the used catchment characteristics. In Section 3 the regression and classification methods are explained. Results are presented in Section 4 and discussed in Section 5.

2 Data

2.1 Study Area

This study is carried out in Piemonte and Valle d'Aosta Regions (North-Western Italy), which have different orographic and climatic characteristics. In this relatively small area (of about 30,000 km^2) the climate varies from the Apennine-Mediterranean one in the South-Eastern hills to the Alpine-Continental one in the Northern Alps mountain range (Claps and Mancino 2002). Low flows regime is characterized by different dry seasons having a slow depletion of the soil reservoir and consequent recession of discharge within the river (Vezza et al. 2009). In the Alpine areas, low flows occur during winter and are affected by snow accumulation and freezing processes. Instead in the Apennine-Mediterranean areas, Summer/Autumn low flows are normally due to aquifers recharge and occur during dry periods when evaporation exceeds precipitation. For this reason an analysis of low flows regime in this territory is both complex and interesting. We use data of catchment areas between 21 and 1,800 km^2, elevations range from 106 m to 4,725 m a.s.l. and mean annual precipitation from a minimum of about 800 mm in South-Eastern hills to a maximum of more than 2,000 mm in Northern mountainous areas. All selected

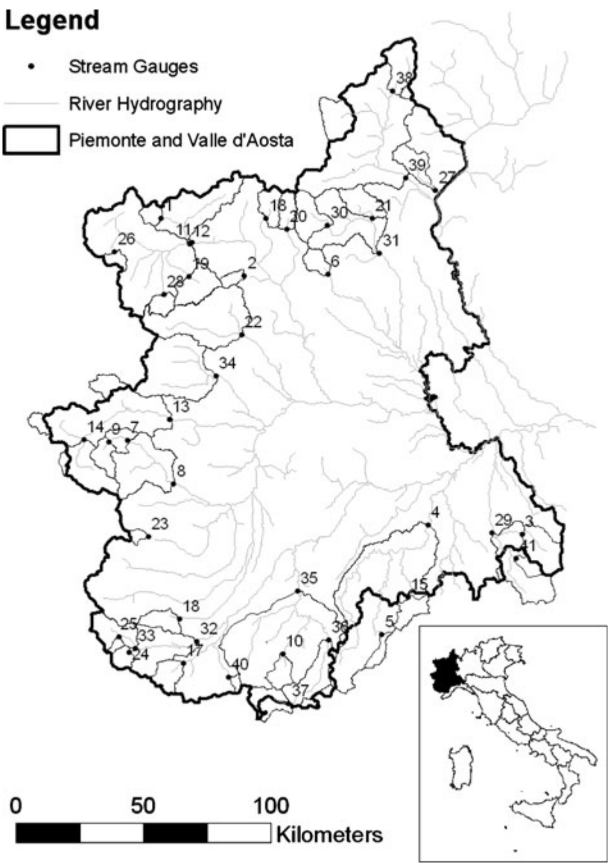

Fig. 1 River network and selected stream gauges in North-Western Italy

catchments cover a total area of more than 12,000 km^2, which is 37% of the entire region. Figure 1 shows the spatial distribution of stream gauges considered in this study and the associated catchment boundaries, while Table 1 lists, for each of them, the related catchment area, the mean annual runoff (MAR), the specific discharge q_{95}, both expressed in $ls^{-1}km^{-2}$ and the time series length.

Table 1 Stream gauges in North-Western Italy

Code	Gauge name	Area(km^2)	MAR($ls^{-1}km^{-2}$)	q_{95}($ls^{-1}km^{-2}$)	Years	Length
1	Artanavaz St.Oyen	70.90	32.44	10.65	1952-67	16
2	Ayasse Champorcher	40.60	39.89	3.43	1950-73	22
3	Borbera Baracche	201.80	24.70	2.65	1942-61	14
4	Bormida Cassine	1,523.80	16.17	0.98	1947-58	12
5	Bormida Mallare Ferrania	49.88	30.60	1.39	1942-56	15
6	Cervo Passobreve	75.00	46.33	6.72	1942-55	14
7	Chisone Fenestrelle	156.75	20.74	4.53	1942-53	10
8	Chisone S.Martino	581.00	22.01	5.15	1942-71	29
9	Chisone Soucheres Basses	91.94	25.97	5.51	1959-71	12
10	Corsaglia Molline	88.94	33.87	3.90	1942-59	18
11	Dora Baltea Aosta	1,823.80	28.48	6.33	1942-55	10
12	Dora Rhemes Pelaud	54.10	46.07	10.98	1942-55	14
13	Dora Riparia Oulx	254.31	21.02	6.71	1943-56	10
14	Dora Riparia S.Antonino	992.56	18.74	9.01	1942-53	10
15	Erro Sassello	82.69	27.97	2.48	1945-60	16
16	Evancon Champoluc	104.90	30.98	5.10	1949-75	27
17	GessoValletta S.Lorenzo	110.44	43.89	10.35	1952-64	10
18	Grana Monterosso	103.25	25.72	5.55	1942-75	32
19	Grand'Eyvia Crétaz	178.60	35.17	3.87	1952-67	16
20	Lys Gressoney	90.50	43.03	6.35	1942-53	10
21	Mastallone Ponte Folle	146.88	50.74	4.95	1942-65	22
22	Orco Ponte Canavese	614.50	32.79	9.66	1942-75	29
23	Po Crissolo	37.50	39.76	11.89	1943-73	28
24	Rio Bagni Bagni Vinadio	61.63	39.35	9.05	1942-56	11
25	Rio Piz Pietraporzio	21.44	40.33	10.04	1942-56	15
26	Rutor Promise	45.60	52.26	5.67	1942-67	20
27	S.Bernardino Santino	118.81	54.86	8.87	1957-69	12
28	Savara Eau Rousse	83.90	34.21	1.08	1944-62	17
29	Scrivia Serravalle	616.13	26.22	1.15	1942-63	14
30	Sesia Campertogno	169.88	40.43	3.99	1942-52	11
31	Sesia Ponte Aranco	702.88	45.28	5.33	1942-51	10
32	Stura Demonte Gaiola	560.06	32.06	7.83	1942-65	11
33	Stura Demonte Pianche	179.94	29.33	9.36	1942-55	14
34	Stura Lanzo Lanzo	576.94	34.56	7.85	1942-75	33
35	Tanaro Farigliano	1,516.06	24.61	4.81	1942-75	33
36	Tanaro Nucetto	375.63	28.60	4.07	1942-65	22
37	Tanaro Ponte Nava	147.63	32.66	3.48	1942-68	24
38	Toce Cadarese	189.69	49.82	16.56	1957-75	18
39	Toce Candoglia	1,539.81	43.82	15.34	1943-64	21
40	Vermenagna Limone	57.44	35.77	8.44	1942-56	15
41	Vobbia Vobbietta	56.88	26.48	1.46	1956-67	12

As characteristic unit runoff, MAR (Mean Annual Runoff) and q_{95} are expressed in $ls^{-1}km^{-2}$ along with the time series length

2.2 Discharge Data

Stream flow data series are considered reliable according to the following conditions: (i) dams absence in the upstream part of the catchment, (ii) a minimum of 10 years of daily stream flow registration and (iii) no relevance of abstractions or karst effects during the low flows periods (Vezza et al. 2009). Considering 41 stream gauges, we use daily discharge data series between 1942 and 1975, for which the longest and continuous time series are available from the Italian Hydrographic Service (closed in 1985). The length of streamflow data series is related both on the data availability and on two previous literature studies carried out in Italy (Castellarin et al. 2004 and Ganora et al. 2009) showing that five years of observed streamflows are generally sufficient to obtain good estimates of the long term flow duration curve. Furthermore, in Laaha and Blöschl (2005) the authors observed that, on average, 1 year of continuous streamflow data measurement clearly outperforms the more sophisticated regionalization method in the assessment of the specific discharge q_{95}. In regional analysis, the uncertainty due to regional variability is much more important than the uncertainty due to sample variability (i.e. to the length of the observed data).

Because of its relevance for multiple topics of water resources management (Smakhtin 2001), we use the low flows index q_{95}, i.e., the discharge exceeded on 95% of all days of the measurement period, as a reference for low flow regime. As mentioned in Vezza et al. (2009), q_{95} (q_{347} using days as frequency, Aschwanden and Kan 1999) is standardized by the catchment area expressing specific runoff and making it comparable across scales. Laaha and Blöschl (2006a) suggested to split the nested catchments into sub-catchments between subsequent stream gauges to avoid problems of dependence between the time series. We however do not use the same procedure because the number of nested catchments is small and because some subsequent gauges have temporally discordant time series. This introduces a problem of spatial statistical dependence of the low flow data, but errors may be larger if the low flow characteristics are estimated from differences of the stream flow records at two gauges. As reported in Laaha and Blöschl (2006b), if the errors of the upstream and downstream gauges are assumed normally distributed and independent, then the error variances are additive and can cause a lager error in the estimates.

2.3 Catchment Characteristics

In this study 28 morphoclimatic watershed characteristics are used, giving synthetic information of the shape of the basin surface, the nature of the soil and vegetation, the topography and climate (Table 2). Due to the limited availability and low spatial accuracy of digital geological maps, geological variables are not considered and land use parameters, the Thornthwaite moisture index, runoff curve number (USDA 1986) and the drainage density are included in the analysis because of their relationship with geology, soil infiltration rate and vegetation type distribution (see Gustard and Gross 1989, for a similar approach).

Drainage basin descriptors are divided into different categories explained using a capitol letter: catchment area A, elevation H, physiographic slope S, orientation

Table 2 Catchment descriptors included in the regional regression analysis

Symbol	Units	Description	Min.	Mean	Max.
A	10^1 km^2	Catchment area	2.14	35.35	182.38
A_{2000}	%	Catchment area above 2000 m	0.00	44.03	97.80
H_{max}	10^2 m	Maximum elevation	9.99	30.56	47.25
H_{min}	10^2 m	Minimum elevation	1.06	8.34	18.80
H_{med}	10^2 m	Mean elevation	4.81	17.76	27.43
H_{range}	10^2 m	Range of altitude	4.81	22.23	42.73
S	%	Mean slope	20.20	45.28	63.00
S_{ind}	%	Mean slope independent from DEM resolution	0.80	15.53	38.70
S_{LDP}	%	Mean slope of the longest drainage path	5.80	18.36	29.30
O	deg	Main catchment orientation angle	1.01	126.15	355.84
O_{NORD}	–	Northing (cosine of O)	−0.81	0.43	1.00
O_{EST}	–	Easting (sine of O)	−1.00	0.20	1.00
LAT	10^4 m	Centroid latitude	33.00	39.39	50.84
$LONG$	10^5 m	Centroid longitude	48.86	49.90	51.35
W_{DD}	$kmkm^{-2}$	Stream network density	0.52	0.59	0.74
W_{RL}	10^2 m	Length of the main river	7.17	31.93	133.85
W_{LCS}	10^2 m	Mean length of watershed sides	60.69	74.72	87.06
W_{SF}	–	Watershed shape factor	0.08	0.30	0.65
W_{CR}	–	Watershed circularity ratio	0.24	0.49	0.74
L_U	%	Urbanised areas	0.00	0.11	0.75
L_F	%	Forested areas	0.47	46.94	99.96
L_{CG}	%	Crop and grassland	0.04	11.08	53.21
L_R	%	Wasteland (rocks)	0.00	41.83	99.35
L_W	%	Wetland	0.00	0.04	1.17
L_{CN}	–	Runoff curve number	26.32	42.19	50.06
C_P	10^2 mm	Mean annual precipitation	8.41	12.62	21.13
C_{IT}	–	Thornthwaite moisture index	0.04	0.89	1.92
C_{IB}	–	Budyko aridity index	0.45	0.85	1.20

Units are chosen to give similar ranges for all characteristics

O, watershed parameters W, land use L and climatic parameters C. Table 2 shows a summary of these catchment characteristics. For the descriptors not directly defined in Table 2 in Vezza et al. (2009) is provided a detailed explanation.

3 Methods

3.1 Regional Regression Analysis

Regional regression is performed building a multi-regressive model that relates the q_{95} (dependent variable) to morphoclimatic descriptors (independent variables) to select the most influential descriptors for low flows regionalization. Compared to Laaha and Blöschl (2006a) and Engeland and Hisdal (2009) this paper goes beyond the stepwise regression by using a more comprehensive multiregressive approach. The models performance coming from 4 different transformations of the dependent variable (q_{95}) were used to avoid heteroscedasticity and non-normality of the residuals of the regressions (Viglione et al. 2007).

$$q_{95} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{p-1} x_{p-1} + \epsilon; \tag{1}$$

$$\sqrt{q_{95}} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{p-1} x_{p-1} + \epsilon; \tag{2}$$

$$\sqrt[3]{q_{95}} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{p-1} x_{p-1} + \epsilon; \tag{3}$$

$$\ln q_{95} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{p-1} x_{p-1} + \epsilon. \tag{4}$$

where: x_i are the morphoclimatic descriptors and β_i are the regression coefficient. The Ordinary Least Squares technique is used to estimate the coefficients β_i (e.g. Montgomery et al. 2001). While the stepwise regression approach includes models in which the choice of predictive variables is carried out by an automatic procedure, in this paper all regression models are attempted with $k2^h$ model forms (where k is the number of forms, as expressed in Eqs. 1–4, and h is the number of candidate regression parameters). Hence, for each model we consider 4 types of regression along with 28 morphoclimatic variables (see Section 2.3), for a total of over 1 million models. The R statistical computing software, and in particular the Non-supervised Regional Frequency Analysis (nsRFA library, Viglione 2006–2010) is used for the computation of statistical indices.

According to Vezza et al. (2009), for all regression models, a combination of all morphoclimatic variables is attempted, satisfying the following assumptions: the absence of multicollinearity, the significance of the independent variables, the homoscedasticity and normality of residuals.

The absence of multicollinearity is checked with the Variance Inflation Factor (VIF, see e.g. Montgomery et al. 2001), while the homoscedasticity and normality of residuals are checked by diagnostic graphs as showed in the results section. The Anderson-Darling test (e.g. Laio 2004) is also used to check the normality of the residuals. A model is finally discarded if, at least, one of the independent variables resulted to be non-significant according to the Student t test at a 95% significance level.

The R^2_{adj} (the adjusted coefficient of determination) is used to assess the descriptive power of each regression and it is defined as (for Eq. 4):

$$R^2_{adj} = \frac{(n-1)\sum_{i=1}^{n}(q_{95,i} - \hat{q}_{95,i})^2}{(n-p)\sum_{i=1}^{n}(q_{95,i} - \bar{q}_{95,i})^2} \tag{5}$$

where: n is the number of considered stations; p is the number of estimated coefficients; $q_{95,i}$ and $\hat{q}_{95,i}$ are the measured and estimated mean annual flow at the i-th site and $\bar{q}_{95,i}$ is the average of the mean annual flows for all considered gauges. For Eqs. 5, 6 and 7 $q_{95,i}$, $\hat{q}_{95,i}$ and $\bar{q}_{95,i}$ are substituted by their transformations.

This paper uses a not common approach to multiple regression by employing different transformations of the dependent variable. The determination coefficient R^2_{adj} is useful to choose the best model among the ones belonging to a given class (Eqs. 1 or 2 or 3 or 4) but cannot be used to compare models of different nature. To this purpose a cross-validation method is carried out, computing the RMSE (Root Mean Square Error) on the residuals. Furthermore, cross-validation is a full emulation of the case of model application in ungauged sites (see Section 3.3.2).

3.2 Classification Methods

3.2.1 Seasonality Indices—SI

As shown in the Austrian study, the seasonality indices approach (SI) has a potential in identifying homogenous groups of catchments using differences in seasonal low flow processes between catchments (Laaha and Blöschl 2006a). Engeland and Hisdal (2009) compared a regional regression model based on seasonality with a regional rainfall-runoff model in Norway for regionalizing low flows and found that the first one performs better than the second. Laaha and Blöschl (2006b) used three indices to investigate the low flows seasonality. The first one is the Seasonality Ratio (SR) which expresses the ratio between summer (q_{95_s}) and winter (q_{95_w}) low flows. From April 1st to November 30th daily discharge time-series are considered as summer discharges and from December 1st to March 31st as winter discharges. Values of $SR > 1$ indicate the presence of a winter low flows regime and values of $SR < 1$ indicate the presence of summer low flows regime. The second seasonality parameter is composed by two indices θ and r (Laaha and Blöschl 2006b). These represent the mean day of occurrence of low flows. The parameter θ is a circular statistic. Its values range between 0 and 2π, explaining the q_{95} mean day of occurrence (e.g., $\theta = 0$ relates to January 1st, $\pi/2$ relates to April 1st, π relates to July 1st and $3/2\pi$ relates to October 1st). The parameter r describes the variability of low flows seasonality, ranging from zero to unity, where $r = 1$ corresponds to strong seasonality (all low flows events occurred on exactly the same day of the year) and $r = 0$ to no seasonality (low flows events are uniformly distributed over the year). The third seasonality index is expressed with seasonality histograms based on a monthly scale. The columns of histograms represent the frequency of discharges below the threshold q_{95} over time. Once the three indices are calculated for each catchments, they are plotted in the geographic space to delineate homogeneous regions in terms of low flows behavior (Fig. 3). Finally restricted regression models for each sub-region are performed.

3.2.2 Classification and Regression Trees—CRT

The Classification and Regression Trees approach is a classification method which uses historical data to construct the so-called decision trees. For building decision trees, CRT splits a learning sample (low flows and catchment characteristics) by using an algorithm known as binary recursive partitioning (Breiman et al. 1984). CRT can easily handle both numerical and categorical variables. Classification trees operate on categorical variables while regression trees operate on continuous variables. CRT methodology consists of three parts: (i) Construction of maximum tree (ii) Choice of the right tree by pruning algorithm; (iii) Classification of unmeasured data using constructed tree.

Building the maximum tree implies to use a splitting rule dividing the data set into two parts by maximizing the homogeneity in the two child nodes (minimize the deviance of the node, i.e. the sum of the squared differences between observed values of q_{95} and the mean of the node). This splitting or partitioning starts from the most important variable to the less important ones and it is applied to each of the new branches. The tree stops growing when each terminal node consists of one single observation. Having potential problems with such overfitting, the CRT algorithm uses tree optimization for pruning back the tree and determine the optimal number of nodes (Breiman et al. 1984). The optimal number of nodes is determined by a cross-validation procedure splitting the data set into 10 equally sized parts and subsequently uses nine parts for calibration and one part for validation. This procedure, called 10-fold cross-validation, is based on minimizing the average prediction error. The CRT algorithm has a very good performance in catchments classification if one is interested in finding groups that are most distinct in terms of both catchment characteristics and low flow catchment response (Laaha and Blöschl 2006a).

The algorithm has a number of advantages over other models: the CRT is non-parametric, is invariant to monotone transformations of its independent variables, easily handles outliers and noisy data isolating them in a separate node and trees obtained are readily interpretable (Breiman et al. 1984). The main weakness of this method consists of having unstable results with modification of learning sample (the structure of the tree may change when models are refitted for subsets of the data). According to Laaha and Blöschl (2006a) a classification tree is fitted to the group names of the regression tree as categorical dependent variable, which exhibits an identical structure to the regression tree, but has the advantage of producing the same group names for various data subsets. For classification trees the splitting rule consists of the maximization of change of impurity function $\Delta i(t)$:

$$\Delta i(t) = i(t_p) - P_l[i(t_l)] - P_r[i(t_r)] \tag{6}$$

where t_p is the parent node and $P_l[i(t_l)]$ and $P_r[i(t_r)]$ are the probabilities of the left and right child nodes respectively. Breiman et al. (1984) mentioned 5 different types of impurity function: Gini and Twoing splitting rules, Enthropy rule, χ^2 rule and maximum deviation rule. Anyway, the authors proved that the final tree is insensitive to the choice of the rule. Also for classification trees a cross-validation procedure is needed to find the best tree size. In this case, the quality of the global tree approximation is assessed by the misclassification error, which is the ratio of misclassified catchments and all classified catchments.

As the dependent variable (q_{95}) needs to be normally distributed for optimal tree construction, we examine the distribution of four transformation of q_{95} with the Anderson-Darling normality test. To build the regression tree we use a square-root transformation of q_{95} that yields a distribution with the best results in passing the normality test. The final step of estimating low flows for the ungauged site of interest is to apply a restricted regional regression model to each group obtained.

3.2.3 *Weighted Cluster Analysis—WCA*

According to Nathan and McMahon (1990) procedures, the WCA consists of the following steps:

1. Apply an overall regression model using standardized catchments characteristics, and weight the most relevant descriptors according to the magnitude of their β-coefficients;
2. Run a number of cluster analysis by different measures of similarity and linkage methods using the weighted catchment characteristics;
3. Plot Andrews curves for each cluster;
4. Identify by visual assessment the set of clusters exhibiting the least within-group variation;
5. Remove outliers if needed and refine the optimum grouping obtained.

We compare Ward's method and several combinations of linkage methods (single linkage, average linkage and complete linkage) using different distance measures (Euclidean distance and Manhattan distance) for different numbers of clusters. To display multivariate data, Andrews plots are used to identify the most appropriate method by visual assessment. In Andrews plots, a point in multi-dimensional space $x_Z[x_1, x_2, \ldots, x_n]$ is represented by a function defined as:

$$F(t) = \frac{x_1}{\sqrt{2}} + x_2 \sin t + x_3 \cos t + x_4 \sin 2t + x_5 \cos 2t + \ldots \tag{7}$$

plotted over the range of $-\pi \leq t \geq \pi$. These plots can be used to both detect groups of similar observations and identify outliers in multivariate data. For each cluster, observations t that are close to one another remain close together. To allocate ungauged catchments to each group (Nathan and McMahon 1990) proposed comparing the Andrews curve of an ungauged catchment with the mean curve of each cluster, since regions obtained by the cluster analysis approach are generally discontiguous in space. As a final step, again, the low flow value for the site of interest is estimated from multiple regressions between observed low flows and catchment characteristics fitted to each of the regions independently.

3.2.4 *Residual Pattern Approach—RPA*

The residual pattern approach to catchment grouping consists of three steps:

1. Perform stepwise regression to obtain a global regression model;
2. Plot the residuals from the global regression model in the geographic space;
3. If residual patterns are apparent, delineate contiguous regions of similar sign and magnitude of residuals.

To avoid over-fitted models, we use a parsimonious model resulting in 4 catchment characteristic and producing clearer residual patterns. The main problem of this technique consists of extending the initial model to the entire domain of interest. Using this approach shapes of regions can be artefact and the regional regression model may have little physical meaning (Laaha and Blöschl 2006a).

3.3 Assessment of the Regional Model

3.3.1 Assessment of Classification Alone: ANOVA Test

To explain how classification methods describe the spatial variability of specific low flow discharges q_{95}, one-factorial analysis of variance (ANOVA) is used. The ANOVA may be interpreted as an assessment of a simple regionalization model where predicted q_{95} (dependent variable) is simply the average low flow discharge in each group of a classification and the classification number is the indipendent variable. The goodness-of-fit measure R^2_{ANOVA} (coefficient of determination) of this model is the ratio of the variance explained by the classification and the total variance of low flows.

3.3.2 Cross-validation

The value of the classification methods for estimating low flow characteristics at ungauged sites cannot be fully assessed by goodness-of-fit statistics (e.g. coefficient of determination R^2_{adj}). We use a cross-validation procedure as the advantage over other techniques of assessing predictive errors is its robustness and its general applicability to all regionalization models. Cross-validation is hence an emulation of the case of ungauged sites. The $RMSE_{CV}$ is defined as the square-root of the average residual square error V_{CV}:

$$RMSE_{CV} = \sqrt{V_{CV}} = \sqrt{\frac{1}{n}\sum_{1=1}^{n}(\hat{q}_{95,i} - q_{95,i})^2} \tag{8}$$

where $\hat{q}_{95,i}$ is the estimated value of the i-th dependent variable obtained using a model estimated with all the observations except the i-th one. It is also possible to define the coefficient of determination based on cross-validation as:

$$R^2_{CV} = \frac{var(q_{95}) - V_{CV}}{var(q_{95})} \tag{9}$$

For each class the multi-regressive model based on the best performances in terms of R^2_{adj}, with the lower $RMSE_{CV}$ and the bigger R^2_{CV} (the best model) and with the use of the most commonly-available parameters (the simplest model) is chosen. The selected models are checked with respect to the assumptions underlying the regression analysis (see Section 3.1).

4 Results

4.1 Global Regression Model

An overall global regression model is fitted to all 41 catchments. Best regressions are chosen on the basis of the criteria discussed in paragraph 3 and considering all the possible linear regression models. Figure 2 shows the four different transformations of q_{95} used to build a global regression model. The value of the Anderson-Darling test statistic A is reported along with the associated p-value. The hypothesis of normality is rejected if the p-value is lower than or equal to 0.05 or the parameter A

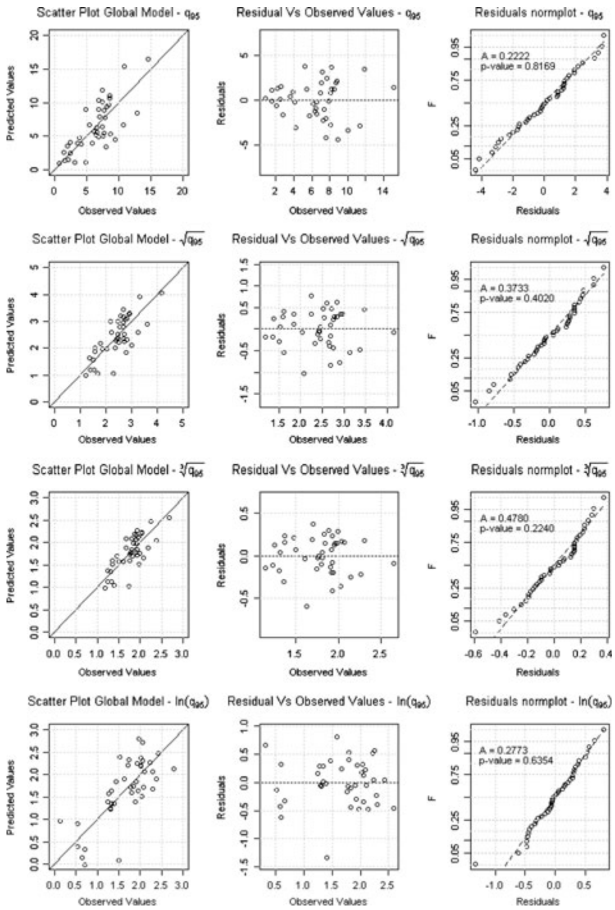

Fig. 2 Global regression model: diagnostic plots for different transformations of q_{95} useful to avoid problems of heteroscedasticity and non-normality of the regressions residuals. The Anderson-Darling normality test rejects the hypothesis of normality when the p-value is less than or equal to 0.05 or the parameter A is bigger than 0.75. For the global model the best result is obtained by using q_{95} not transformed

is bigger than 0.75. The non-transformed q_{95}, which gives the best Anderson-Darling test result, is chosen as global model. Table 3 outlines the best global regressions obtained for each model class, along with R^2_{adj}, $RMSE_{CV}$ and the cross-validation coefficient of determination R^2_{CV}. The last two statistic are obtained from cross-

Table 3 Global regression models

Regression model	R^2_{adj}	$RMSE_{CV}$	R^2_{CV}
$q_{95} = -7.31 + 0.504(H_{med}) - 0.337(S_{LDP}) + 0.149(L_{CG}) + 0.737(C_P)$	0.643	2.420	0.572
$\sqrt{q_{95}} = -0.504 + 0.107(H_{med}) - 0.0639(S_{LDP}) + 0.0288(L_{CG}) + 0.149(C_P)$	0.657	2.425	0.571
$\sqrt[3]{q_{95}} = 0.283 + 0.0546(H_{med}) - 0.0315(S_{LDP}) + 0.0143(L_{CG}) + 0.0751(C_P)$	0.654	2.470	0.555
$lnq_{95} = 2.631 + 0.0225(H_{range}) - 0.0749(LAT) + 0.0212(L_{CG}) + 0.0982(C_P)$	0.630	3.138	0.302

validated residuals and, therefore, are representative of the prediction of low flows in ungauged catchments.

Though differences between models are marginal, the global regression shows the best relative performance $R^2_{CV} = 57\%$, corresponding to $RMSE_{CV} = 2.420\ ls^{-1}km^{-2}$, and the best results for the residuals normality test when considering q_{95} without transformation. In this study, model assumptions (normality of residuals and heteroscedasticity) are carefully checked by three diagnostic graphs: scatter plots of observed versus predicted values, residual plot as a function of observed values and normal probability plots of residuals (Fig. 2). Considering the performance of the q_{95} global model (without transformation), the outliers do not tend to increase with q_{95} and the residuals can be considered homoscedastic. Cross-validated residual in normal probability plot are approximately normally distributed performing the best results in the Anderson-Darling test. Mean elevation (H_{med}), slope of longest drainage path (S_{LDP}), proportion of crop and grasslands (L_{CG}) and mean annual precipitation (C_P) demonstrate are identified to be the most significant variables for the regionalization of low flows indices.

4.2 Seasonality Indices—SI

The first approach to catchment grouping considered in this study is based on types of low flow seasonality as defined by Laaha and Blöschl (2006a). Figure 3 represents the three seasonality indices used to group catchments. Considering the low flows occurrence, the seasonality indices suggest that the study area can be classified into two main units. Group 1 is the Apennine-Mediterranean area where low flows normally occur during summer and Group 2 is the Alpine region, characterized by

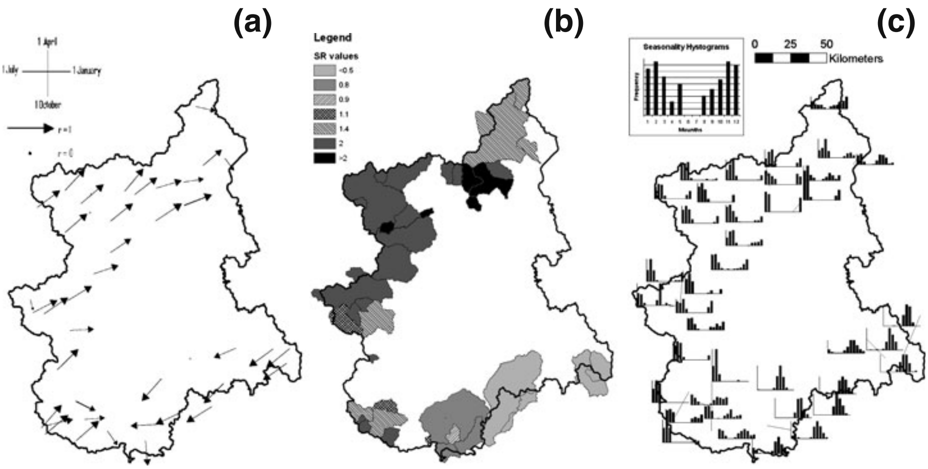

Fig. 3 **a** Variability and mean day of occurrence of q_{95}. Long arrows indicate strong seasonality and their direction represents the mean day of occurrence; **b** Seasonality ratio (SR) between summer and winter low discharges. $SR > 1$ indicates a winter low flows regime and $SR < 1$ indicates a summer low flows regime; **c** Non-exceedance frequency histograms (SHs) of specific low flow q_{95} based on monthly scale

winter low flows. Regions with approximately homogeneous seasonality are shown in Fig. 4a.

The ANOVA test shows that this classification method explains 37% of the variance only. This low value is not surprising, given that the SI method does not optimize the similarity between q_{95} of different catchments but is intended to reflect hydrological processes (we expect that processes leading to winter low flows are different from those leading to summer low flows). Indeed, also in Austria (see, Laaha and Blöschl 2006a) the variance explained by the classification with seasonality indices was only 34% of the total variance. Since all regions are contiguous, the allocation of ungauged sites is well defined by their location and no reclassification is needed in the cross-validation procedure. Regional regressions are fitted independently to each of the two regions and results are summarized in Table 4. In Group 1 (Apennine-Mediterranean region), the models fit well, with coefficients of determination equal to 82%. The regression model for the Alpine region (Group 2), instead, exhibits a coefficient of determination $R^2_{adj} = 49\%$. This low coefficient is not surprising as different types of catchments, differing for mean annual rainfall, topography and climate, are lumped into a single group. Finally, grouping catchments

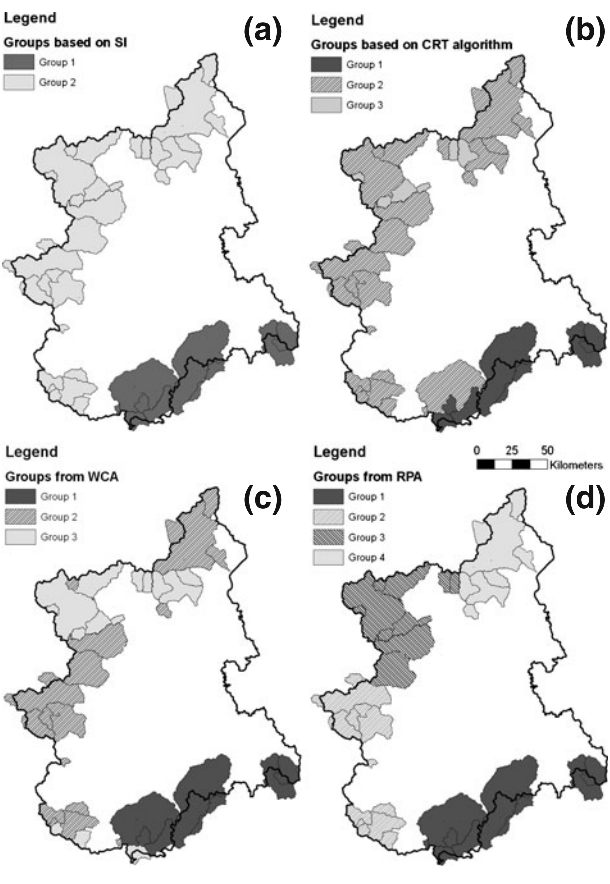

Fig. 4 Groups of catchments based on the four grouping methods. **a** refers to Seasonality Indices method; **b** to Classification and Regression Tree approach; **c** to Weighted Cluster Analysis and **d** to Residual Pattern Approach

Table 4 Restricted models based on the four grouping methods

Method	Group	Regression model	R^2_{adj}	$RMSE_{CV}$	R^2_{CV}
SI	1	$\sqrt{q_{95}} = 0.535 + 0.0555(H_{max}) + 0.0211(L_R)$	0.822	2.317	0.608
	2	$q_{95} = -10.8 + 0.597(H_{med}) - 0.348(S_{LDP}) + 0.196(L_{CG}) + 0.833(C_P)$	0.491		
CRT	1	$\sqrt[3]{q_{95}} = 0.773 + 0.0297(H_{max})$	0.613	2.072	0.687
	2	$\sqrt[3]{q_{95}} = -0.211 + 0.0577(H_{med}) + 0.0061(W_{RL}) + 0.0107(L_{CG}) + 0.0549(C_P)$	0.426		
	3	$\sqrt[3]{q_{95}} = 6.259 - 0.403(H_{min}) + 0.0545(S_{LDP})$	0.984		
WCA	1	$\sqrt[3]{q_{95}} = 0.710 + 0.0344(H_{max})$	0.605	2.214	0.642
	2	$q_{95} = -17.9 + 0.292(H_{max}) + 0.468(LAT)$	0.490		
	3	$q_{95} = 41.0 - 0.512(LAT) - 0.3787(L_{CN})$	0.470		
RPA	1	$\sqrt{q_{95}} = 0.535 + 0.0555(H_{max}) + 0.0211(L_R)$	0.822	2.534	0.531
	2	$q_{95} = -4.57 + 0.332(H_{range}) + 0.394(S_{LDP}) -0.068(L_F)$	0.771		
	3	$q_{95} = 14.5 - 0.104(L_R)$	0.538		
	4	$\sqrt[3]{q_{95}} = 1.67 + 0.0186(L_{CG})$	0.548		

SI refers to Seasonality Indices method; CRT to Classification and Regression Tree approach; WCA to Weighted Cluster Analysis and RPA to Residual Pattern Approach

into two sub-regions based on seasonality leads to two separate regressions having an overall model performance $R^2_{CV} = 61\%$ and $RMSE_{CV} = 2.317\ ls^{-1}km^{-2}$. This is a better prediction performance compared to results of the global regression models. Laaha and Blöschl (2006a) explained the 70% of the variance of q_{95} in Austria, outlining that delineating regions based on seasonality of low flows provides a very efficient catchments classification. It is interesting to note in regression model of the Group 2 (Alpine region) mean elevation (H_{med}), slope of longest drainage path (S_{LDP}), proportion of crop and grasslands (L_{CG}) and mean annual precipitation (C_P) demonstrate to be the most significant variables, as in the global regression model. In Group 2 (Apennine-Mediterranean area) the most important variables are the maximum altitude (H_{max}) and the proportion of rocks (L_R) that are related to topography and especially to the presence of snowpack storage in the upper part of the catchment area.

4.3 Classification and Regression Trees—CRT

In the classification and regression tree approach the dependent variable (q_{95}) needs to be normally distributed. We use the square-root transformation of the specific low flow discharge ($\sqrt{q_{95}}$) as target variable, as this is the closest transformation to the normal distribution according to the Anderson-Darling normality test. 28 catchments characteristics are used as descriptive variables and the optimal tree size is determined by 10-fold cross-validation. Fitting the regression tree to the data, it is possible to define an initial regression tree that has to be pruned back till the lower total prediction error. Results indicate that the optimum size consists of three nodes (Fig. 5a) performing the lowest prediction error, that is where the cross-validated total deviance of the tree is at its minimum.

The obtained regression tree divides the study domain into three regions represented in Fig. 5a by terminal nodes. The resulting classification uses for partitioning

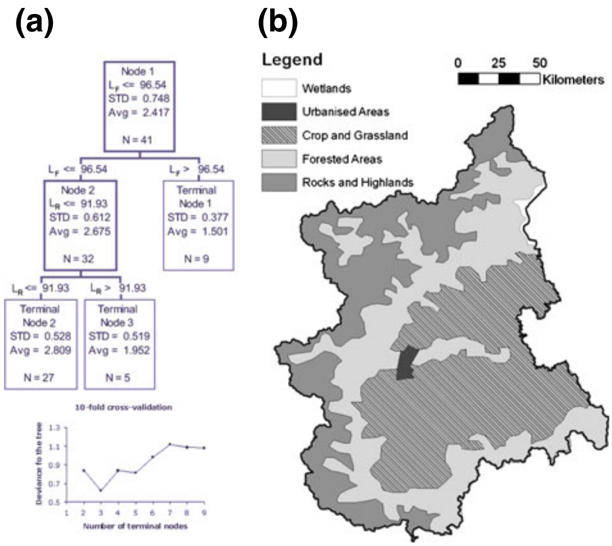

Fig. 5 **a** Regression Tree obtained using $\sqrt{q_{95}}$ as target variable. Terminal nodes represent groups of catchments. Avg and STD represent respectively means and standard deviations of the node. N indicates the number of catchments within groups. The optimal number of terminal nodes is defined calculating the minimum value of cross-validated deviance of the tree; **b** Simplified land use map useful to allocate ungauged catchments into sub-regions defined by the Classification and Regression Tree algorithm

land use parameters, in particular the percentage on forested and rocks areas (L_F and L_R respectively), creating groups of catchments having similar low flows characteristics (Fig. 4b). Land use is significant in low processes affecting evapotranspiration and soil infiltration rate. In particular they are related to water losses in low flows discharges during dry periods. Forested areas (Group 1 with $L_F > 96.5\%$) are located in the Apennine hilly zones and piedmont areas. Those catchments are characterized by a low flow regime with strong drought period ($\bar{q_{95}} = 2.40\ ls^{-1}km^{-2}$) occurring during summer. Group 2 (Alpine region with $L_F \leq 96.5\%$ and $L_R \leq 92\%$) have a specific $\bar{q_{95}}$ discharge, on average, equal to 8.17 $ls^{-1}km^{-2}$ occurring during winter and affected by freezing processes of soils and snow cover. Group 3 ($L_F \leq 96.5\%$ and $L_R > 92\%$) is composed by highlands and rocks areas. These catchments are located in the upper part of the Alps mountain range having a particular low flows regime occurring in winter ($\bar{q_{95}} = 4.08\ ls^{-1}km^{-2}$).

With the one-way ANOVA test, it is possible to estimate the explained variance for the CRT classification, that leads to a result of 69%. This large value means that the CRT approach is an excellent classification method, able to find distinct groups in terms of both low flow catchment response and catchment characteristics (Laaha and Blöschl 2006a). Regression equations are fitted to each region independently (Table 4). Two regions (Group 1 and 3) are well represented by the regression models ($R^2_{adj} = 61\%$ and $R^2_{adj} = 98\%$, respectively). The Alpine region (Group 2) exhibits a moderate model fit equal to 43%. The cross-validation of regional regression estimates based on the regression tree approach is found as $R^2_{CV} = 69\%$. This is significantly better than the estimates from the seasonality indices method where the performance is only $R^2_{CV} = 61\%$. Another advantage of using CRT algorithm consists in easily allocating ungauged catchment into groups: as CRT approach does not need to consider contiguous regions, one can allocate ungauged catchments by using a simplified land cover map (Fig. 5b). With this map, we split our study domain referring to the CRT classification, by using 5 land use classes reported in Table 2. Highlands/moors areas and forested zones will be used to create groups of catchments having similar low flows characteristics. In Group 2 (Alpine region) for the regression model, mean elevation (H_{med}), proportion of crop and grasslands (L_{CG}) and mean annual precipitation demonstrate to be the most significant variables, as in the global regression and seasonality indices method. The only difference is that the slope of longest drainage path (S_{LDP}) is substituted with the river length (W_{RL}). Another parameter that appears again in CRT regression models is the maximum altitude (H_{max}) for Apennine-Mediterranean areas, as already shown using seasonality of low flows. For catchments located in moors and highland the most important variables are the minimum altitude (H_{min}) with a negative influence and the slope of longest drainage path (S_{LDP}) that is related to topography of these particular catchments.

4.4 Weighted Cluster Analysis

According to Nathan and McMahon (1990) we base a global regression model on standardized catchment characteristics (descriptors transformed having zero mean and unit variance) and we find the best regression model defined as:

$$q_{95} = 1.78 + 0.35(H_{med}) - 0.20(S_{LDP}) + 0.18(L_{CG}) + 0.21(C_P) \tag{10}$$

The β-coefficients of catchment characteristics obtained in the regression are used as weights in the weighted cluster analysis. Cluster analysis are carried out combining different distance measures and linkage methods for 3 and 4 clusters of catchments. Andrews curve are used to evaluate the homogeneity of each group. Figure 6 shows the classification based on Ward's method and Euclidean distance which produces the preferable cluster classification, dividing the study domain into three groups. The figure shows the group number, the number of catchments for each group and each line corresponds to one catchment. In group number 2, only two catchments appear to be different from the rest, so we deem the groups sufficiently homogeneous for the further analysis, avoiding any subjective re-classification of outliers.

Results of the ANOVA test show that WCA classification explains 45% of the total spatial variance of q_{95}. This is significantly less than CRT, but it represent a better result compared to the Seasonality Indices approach. By plotting the clusters on a map (Fig. 4c) WCA assigns to the same group catchments located at the opposite

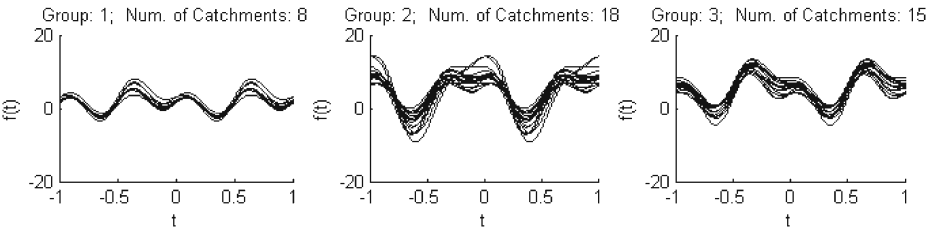

Fig. 6 Defined clusters using the Andrews curves coming from Ward's method and Euclidean distance. Each graph corresponds to one cluster and each line corresponds to one catchment

side of the study domain and with completely different climatic characteristics (e.g. Valle d'Aosta Region, characterized by a typical Alpine climate, and South Piemonte, influenced by the Apennine-Mediterranean one, are included in the same group). WCA divides the Apennines areas (i.e Group 1) from Alpine catchments (Group 2 and 3) like the two previous methods. Within the Alpine region, catchments are scattered in terms of their location especially grouping together those located in Valle d'Aosta Region (Group 3 in North-West). Regression models fitted to each of the regions lead to moderate coefficient of determination R^2_{adj} between 49 to 60% for 3 groups (Table 4). The cross-validation procedure gives a predictive performance equal to 64% and a $RMSE_{CV} = 2.214\ ls^{-1}km^{-2}$. Due to the large R^2_{CV} coefficient, the weighted cluster analysis appears to be useful for delineating regions for the regional regressions. In Group 2 and Group 3 (Alpine region), the centroid latitude (LAT) has some potential in describing low flows regime. Also USGS curve number (L_{CN}) for Group 2 and maximum altitude H_{max} for Group 3 are selected by the regression analysis as important variables. Again, as it is shown in Table 4, the maximum altitude (H_{max}) is the most influential parameter for Apennine-Mediterranean areas.

4.5 Residual Pattern Approach—RPA

The best global regression model fitted to the data is defined by four catchment characteristics: mean elevation (H_{med}), slope of longest drainage path (S_{LDP}), proportion of crop and grasslands (L_{CG}) and mean annual precipitation (C_P). Figure 7 shows the residual map, since the classification method has the preliminary purpose

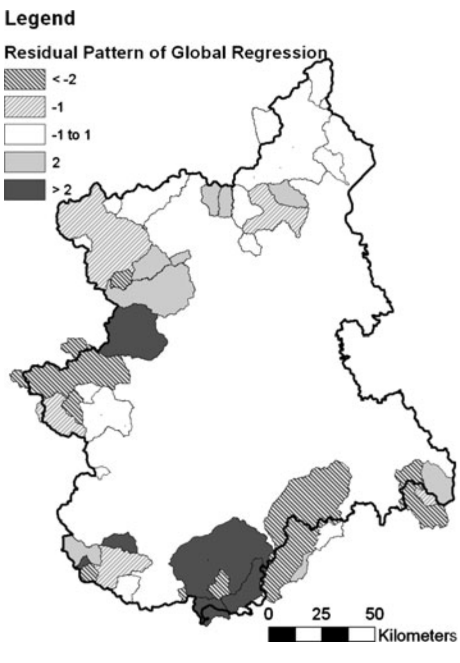

Fig. 7 Residual pattern of the best global regression model. Residuals are divided in 5 classes and plotted in the geographic space

to calculate a meaningful residual pattern within the geographic space. Using the sign and magnitude of residuals it is possible to delineate four regions, used as basis for a regional regression model. Figure 4d shows groups classification defined by the RPA method. The way chosen to split the study domain is similar to other studies carry out in Northern Italy using the same classification technique (Autoritá di Bacino del Fiume Po - Po River Basin Authority 1999).

The coefficient of determination calculated by one-way ANOVA is $R^2 = 40\%$ which means that this classification explains 40% of the total spatial variance of the specific low flow discharges q_{95}. The ANOVA test gives a better result than for the Seasonality Indices approach (37%), but it is worse if compared to the Weighted Cluster Analysis (45%) and especially with the Classification and Regression Tree (60%). For the Residual Pattern Approach, the four restricted models are presented in Table 4. Two of the four regions are poorly represented by the regional models (Groups 3 and 4 with $R^2_{adj} = 55\%$ and $R^2_{adj} = 54\%$ respectively) which suggest that models do not fully capture the predictive performance for ungauged sites. However, the regression model for Group 1 and 2 indicates a good model performance ($R^2_{adj} = 82\%$ for Group 1 and $R^2_{adj} = 77\%$ for Group 2), which suggests that there may be significant heterogeneity of low flow processes within these regions. The predictive performance of the complete regional regression model checked by cross-validation is $R^2_{CV} = 53\%$. This is significantly worst than the coefficient of determination of the classification coming from others methods.

5 Discussion

The regional regression approach, which correlates q_{95} and catchment characteristics, is the most widely used method to estimate low flows in ungauged catchments. The simplest way to regionalize q_{95} is the application of a global regression model to the study domain. The assumption underlying the application of the global model is that all the different processes leading to low flows can be captured by a unique relation, which is also linear. This is a quite strong assumption. Indeed the performance of this method in Piemonte and Valle d'Aosta regions is not optimal: $R^2_{CV} = 57\%$. Like in Laaha and Blöschl (2006a), our results show that classifying the study domain in subregions improves the regionalization of q_{95} through regional regressions.

Over the global model (regression without grouping), the improvement obtained by classification is partly related to the degree of nonlinearity that the grouping methods are likely to capture. Moreover, catchment classification allows to implicitly take into account factors affecting low flows that cannot be easily included in the regression models: i) unknown controls that do not change within the region but across the regions; ii) some predictors can be positively correlated to q_{95} in one region and negatively in another one. Unlike in Laaha and Blöschl (2006a), it appears that, in our particular study domain, delineating regions based on the seasonality of low flows (SI method) is not the best classification method to regionalize q_{95} through regional regressions. The coefficient of determination in the cross-validation mode is $R^2_{CV} = 61\%$. Two other methods perform better than SI: the grouping based on Classification and Regression Trees (CRT) with $R^2_{CV} = 69\%$ (Table 3) and the weighted cluster analysis (WCA) with $R^2_{CV} = 64\%$. Only the performance of the residual pattern approach (RPA) is smaller ($R^2_{CV} = 53\%$), even smaller than a global regression model on the entire study area.

As a final step of assessing the methods of catchment grouping one can examine the scatter plots of predicted vs. observed specific low flow discharges q_{95} (Fig. 8). The scatter plots allow a detailed evaluation of the performance of individual catchments including the existence of outliers and a potential heteroscedasticity of the observations and the predictions. One can observe how the Classification and Regression Trees approach performs best. Overall the four scatter plots of methods is it possible to observe how some catchments influence the final result. In particular considering catchments 38 within Weighted Cluster Analysis scatter plot and catchments 39 for the other three methods, one can observe how the value of q_{95} is underestimated. Having the second best performance, the Weighted Cluster Analysis generally performs quite well but appears slightly inferior to the CRT as far as outliers are not so concerned. The Seasonality Indices and Residual Pattern Approach, as said before, underestimate q_{95} value for catchment 39 and at the same time, overestimate low flows in two and three catchments respectively.

The groups obtained by the classification methods (Fig. 4) are quite similar. All of them identify the Apennine–Mediterranean area in the south-eastern part of the region as a single cluster (with some minor differences). The area is characterized by low flows occurring in summer, from July and September, with a particularly low average value ($\bar{q_{95}} = 2.40\ ls^{-1}km^{-2}$ in the CRT grouping). The streams in this area are in many cases ephemeral, especially for small catchments in the eastern part where q_{95} can be zero. This is not the case of the Tanaro and Vermenagna rivers (West part of the Apennine-Mediterranean area), which has higher mountains upstream (higher orographic precipitation) and a lower proportion of forests (lower evapotranspiration). Here q_{95} is higher and the CRT method allocates it to another

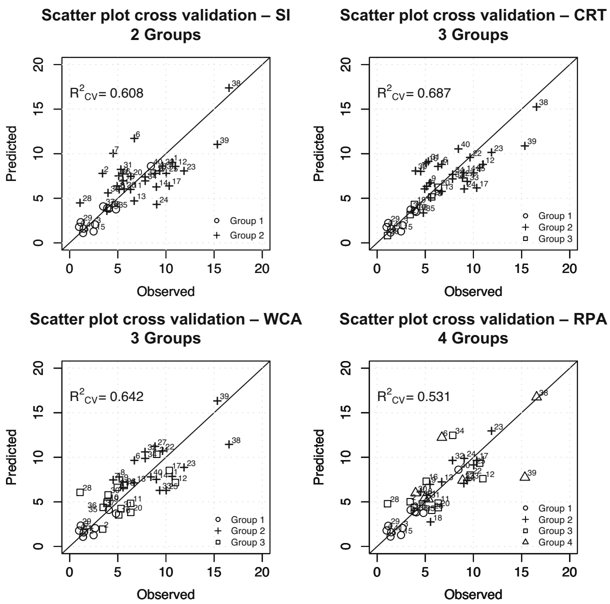

Fig. 8 Cross-validation scatter plots of specific low flow discharges $q_{95}(ls^{-1}km^{-2})$. Each point corresponds to one catchment belonging to a group. In the figure also the catchment code and the overall cross-validation coefficient are shown

group. The classification parameter that characterizes the Apennine-Mediterranean region obtained by the CRT approach is the percentage of forests, which is very high. Actually, we believe that the relatively low value of $\bar{q_{95}}$ in this region is not only related to the high evapotranspiration, but also to the local climate and moderate snowpack storage. In a sense, considering also the similar classification of the other methods, we believe that in this case the proportion of forests L_F (the classification variable of the CRT) also includes information on climate and orographic conditions, which are different to the rest of the study domain.

Looking at the regression model fitted to the Apennine-Mediterranean region identified by the CRT, the only relevant predictor variable is the maximum altitude (H_{max}), which is positively correlated to q_{95}. Note that H_{max} is the most important variable also in the regions obtained by the other grouping techniques (Table 4). This is because, inside the region, high elevation is related to low evaporation and more rainfall, due to orographic effects. In this region, high elevation also means late spring snowmelt and, consequently, higher values of low flows, which happen in summer.

Using the Seasonality Indices, all catchments not belonging to the Apennine-Mediterranean area are included in a single big group, characterized by winter low flows (from December to March), but indeed very heterogeneous. Using the other grouping methods, this area is divided into parts. By the RPA three other regions are identified, which are: the South-Western Alps, characterized by not extremely high mountains and nivo-pluvial streamflow regimes; the Valle d'Aosta Region (including Orco and Stura di Lanzo rivers) with higher mountains and presence of glaciers; and the Northern-Eastern very wet Sesia and Toce watersheds. The RPA is indeed a manual classification, in which the map of residuals of the global regression assists the expert into the delineation of regions. The method is not completely objective and the results reflect the experience of the analyzer. The CRT and WCA classification methods are instead completely objective. They separate the area of winter seasonality of low flows into two groups. Both of them group together catchments of the Valle d'Aosta Region. The WCA groups all of them plus the Sesia catchment and some high elevated watersheds in the South. This classification appears to have a small hydrological sense, assigning to the same group catchments with completely different kind of climate. On the contrary, the CRT groups together only the small catchments located in the highlands and moors in Valle d'Aosta. One of the features of the CRT algorithm is to isolate noisy data in separate nodes and, apparently, this is the reason of the good performance of the CRT in comparison to the SI method.

From an interpretative point of view, the fact that the CRT splits the very elevated small Alpine catchments from the others is very interesting. In these very high catchments, the average q_{95} is particularly low ($\bar{q_{95}} = 4.08\, ls^{-1}km^{-2}$ versus $\bar{q_{95}} = 8.17$ $ls^{-1}km^{-2}$ of the others) because of the retention of solid precipitation in the snow pack and of freezing processes (due to the very high elevations) and also because of no-soil and no relevant storage in groundwater, due to the high percentage of rocks. In fact, the percentage of rocks is the splitter, which allows to identify this region by the CRT. This region is formed by all high elevation catchments and the group has H_{min} and S_{LDP} as descriptors in the linear regression model, where H_{min} is negatively correlated to q_{95}. Anyway, inside the group, elevation still has an important role in explaining the variability of q_{95}, which is related again to the freezing processes in winter. Also, the precipitation at higher elevations is snow in winter, not contributing to streamflow. Regarding the positive coefficient of S_{LDP}, the mean slope of longest drainage path generally has a positive effect on low flows and it is correlated with storage volume in high mountains. The remaining part of the Alpine area (Group 2 of the CRT classification) is still heterogeneous. It is composed of 27 catchments from South-West to North-East of the region with different climatic conditions and, in general, high values of low flows ($\bar{q_{95}} = 8.17\ ls^{-1}km^{-2}$). Given the highest mixture of processes involved, we expect the model for q_{95} to be more complex and harder to interpret than in the other two groups. The following parameters are significant: mean annual precipitation (C_P), mean elevation (H_{med}), river length (W_{RL}) and proportion of crop and grasslands (L_{CG}). The positive relation of precipitation with low flows is obvious. Annual precipitation provides water which is stored in different ways in the catchments (as snow, in groundwater systems, in soil, in lakes, etc.) and which is released at different timescales. The effect of H_{med}, in the Alpine range, is essentially related to the decrease of evaporation. We do not expect the snowmelt to affect the low flows, because these happen from late autumn to late winter. The river length (W_{RL}) is a measure of catchment size. We would expect that larger catchments have larger values of q_{95} because of the positive interactions between the aquifers and the river stream (gaining streams in the valley). A similar result was obtained by Engeland and Hisdal (2009), who found that the catchment area is a good explaining variable for winter low flows in Norway. The proportion of crop and grasslands (L_{CG}) is also positively correlated to q_{95}. The percentage of grass and cropland is inversely proportional to the percentage of forest plus the percentage of rocks. So we would expect that evapotranspiration decreases for increasing L_{CG} (less forests) thus resulting in highest q_{95}. Also high values of L_{CG} result in high infiltration capacity and recharge of groundwater systems, much more than in forests, where also in winter (with low evapotranspiration) water is stored and not released. Aschwanden and Kan (1999), within a study concerning the low flows regionalization for Switzerland, outlined that land use plays an important role in predicting low flows indices, especially considering the characteristics proportion of agricultural areas and pre-Alpine farming structures. If one looks at the regression fitted to Group 2 of the SI method, which is similar to the one obtained by CRT but also includes the small highland catchments, the only difference is that the slope of longest drainage path (S_{LDP}) appears instead of the river length (W_{RL}). The S_{LDP} is inversely proportional to q_{95} and can also be seen as a measure of catchment size, since small alpine catchments have higher slopes than the big ones.

6 Conclusion

In this study a regional regression approach has been applied to estimate the specific low flow index q_{95} in Piemonte and Valle D'Aosta Regions to obtain a predictive operational model for low flows in ungauged catchments, as preparatory reference for the environmental flows assessment at regional scale. The methodology includes the following steps: (i) classification of the study area in hydrologically homogeneous regions; (ii) application of linear regression models in each region to relate q_{95} to catchment and climatic variables. For the first step, we use the four classification methods compared in Laaha and Blöschl (2006a): Seasonality Indices (SI), Classification and Regression Trees algorithm (CRT), Weighted Cluster

Analysis (WCA) and Residual Pattern Approach (RPA). For the second step, compared to Laaha and Blöschl (2006a), we use a more comprehensive multi-regressive approach on different transformations of the dependent variable (q_{95}) and the optimal classification is chosen based on both statistical performance and hydrological interpretation of the model parameters.

From a statistical point of view, the CRT method outperforms the models obtained by the other techniques in terms of explained variance and therefore can be used in Piemonte and Valle d'Aosta for the regionalization of low flows. In addition, we are interested in identifying and understanding the controls on low flow discharges in our study domain by looking at the data. To do that, the results are analyzed trying to interpret the hydrological meaning of the obtained regions and regression models. The splitters used to form regions and the coefficients of the regressions in these regions reveal the following picture: in the South-Eastern Apennine-Mediterranean part of the area, low flows occur during summer with a strong drought period and are mainly due to dry climate, moderate snowpack storage and high evapotranspiration. Inside this region, the elevation of the catchments is important because high elevation is related to low evaporation, more rainfall due to orographic effects and late spring snowmelt. In the small elevated highlands catchments in North-West, low flows are relatively low and occur in winter, because of freezing processes that are more or less effective for different elevations. In the remaining Alpine range, low flows are higher (climate is wetter than in the Apennine area and warmer than in the highlands), occur in winter and vary according to precipitation, elevation (because of evaporation), catchment size (because of interactions with aquifers) and land cover (which controls evapotranspiration, infiltration capacity and recharge of groundwater systems).

We believe that the best classification method is site dependent and can not be chosen a priori. Looking at the results we can state that the use of more than one regionalization technique on the same study area is helpful, not only to identify the best model, but also to interpret the goodness of the results. For instance, all the classification models separate the Alpine from the Apennine-Mediterranean area. Since the models use different discriminant variables to separate these regions (e.g., the percentage of forest, seasonality of low flows, combination of several parameters), it indicates that this classification is indeed robust. As operational procedure for future low flow regionalization studies, we suggest that more methods should be applied to assist the critical analysis of the results.

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