# A national low flow estimation procedure for Austria

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**Abstract** We present a procedure for estimating Q95 low flows in both gauged and ungauged catchments where Q95 is the flow that is exceeded 95% of the time. For each step of the estimation procedure, a number of alternative methods was tested on the Austrian data set by leave-one-out cross-validation, and the method that performed best was used in the final procedure. To maximise the accuracy of the estimates, we combined relevant sources of information including long streamflow records, short streamflow records, and catchment characteristics, according to data availability. Rather than deriving a single low flow estimate for each catchment, we estimated lower and upper confidence limits to allow local information to be incorporated in a practical application of the procedure. The components of the procedure consist of temporal (climate) adjustments for short records; grouping catchments into eight seasonality-based regions; regional regressions of low flows with catchment characteristics; spatial adjustments for exploiting local streamflow data; and uncertainty assessment. The results are maps of lower and upper confidence limits of low flow discharges for 21 000 sub-catchments in Austria.

**Key words** low flows; droughts; regionalisation; prediction of ungauged catchments (PUB); seasonality index; catchment grouping; regional regression; climate variability adjustment; predictive uncertainty

## Une procédure nationale pour estimer les étiages en Autriche

**Résumé** Nous présentons une procédure d'estimation de l'indicateur Q95 d'étiage dans des bassins jaugés et non-jaugés où Q95 est l'écoulement qui est dépassé 95% du temps. Pour chaque pas de la procédure d'estimation, plusieurs méthodes alternatives sont testées sur le jeu de données Autrichien par validation croisée et élimination successive, et la méthode qui donne les meilleurs résultats est utilisée dans la procédure finale. Afin de maximiser la précision des estimations, nous combinons des sources pertinentes d'information composées de longues séries de débit, de courtes séries de débit et de caractéristiques des bassins versants, selon la disponibilité des données. Plutôt que de dériver une simple estimation d'étiage pour chaque bassin, nous estimons les limites de confiance inférieure et supérieure vis-à-vis de l'incorporation de l'information locale dans la mise en œuvre pratique de la procédure. Les composantes de la procédure consistent en des ajustements temporels (climatiques) pour les courtes séries; le regroupement des bassins selon une logique saisonnière en huit régions; des régressions régionales entre les étiages et des caractéristiques des bassins; des ajustements spatiaux pour exploiter les données locales de débit; et une évaluation de l'incertitude. Les résultats consistent en des cartes des limites de confiance inférieure et supérieure des débits d'étiage de 21 000 sous-bassins versants en Autriche.

**Mots clefs** étiages; sécheresses; régionalisation; prévision en bassin non jaugé (PUB); indice de saisonnalité; regroupement de basins versants; régression régionale; ajustement de variabilité climatique; incertitude de prévision

## INTRODUCTION

Estimates of river low flow characteristics are needed for a range of purposes in water resources management and engineering. In water quality management they are used for issuing discharge permits and locating treatment plants; in water supply planning they are used to determine allowable water transfers and withdrawals (Tallaksen & van Lanen, 2004); in hydropower development they are used for determining environmental flows (Gustard *et al.*, 2004); and in an environmental context they are used for streamflow habitat assessment (Jungwirth *et al.*, 2003). Application of the European Water Framework Directive to assess the state of water bodies requires low flow estimates. Several countries have therefore developed national estimation procedures to provide a consistent methodology for determining low flows at gauged and ungauged sites.

*Open for discussion until 1 February 2008* 

The United Kingdom has probably the longest history of national low flow estimation procedures in Europe. In an early low flow study, the *Low Flow Studies Report* (Institute of Hydrology, 1980), relationships between low flow regimes and climatic catchment characteristics were derived. Flow-duration curves standardized by mean flow were found to be related to the characteristic response of a catchment to rainfall, and the gradients of the lognormal flow duration curves indicated a close relationship with catchment geology. As a next step in establishing a national procedure, Gustard *et al*. (1992) developed a global multivariate regression model between standardized low flow characteristics, such as Q95/MQ, and soil characteristics, where Q95 is the flow that is exceeded 95% of the time and MQ is the mean annual discharge. These regressions have been in use by UK agencies since the early 1990s. Later, a pooled regionalisation strategy was adopted (Holmes *et al*., 2002), as the global regression tended to underestimate large values of Q95. In this procedure, Q95 low flows are estimated by a weighted average of standardised Q95 values of 10 gauged reference catchments that are most similar in terms of soil classes. This procedure has been coded into the *Low Flows 2000* software package (Gustard *et al*., 2004), which is currently in use as a national low flow estimation system in the UK. All data and methods are encapsulated in this software, so any analyst will arrive at the same low flow estimate for a particular site. However, it is not straightforward to integrate this procedure with additional, local data not provided by the software.

The national estimation procedure of Switzerland pursues a different strategy (Aschwanden & Kan, 1999a). Low flow regionalisation is based on a regional regression approach. In this approach, regression models between specific low flow q95, i.e. Q95 divided by the catchment area, and catchment characteristics are fitted independently for sub-regions of the study area that are deemed to be homogeneous in terms of low flow processes. The delineation of sub-regions in Switzerland is based on the residual pattern approach (Hayes, 1992). A map that combines low flow measurements of gauged catchments and low flow estimates of selected ungauged catchments was compiled and published in the *Hydrological Atlas of Switzerland* (Aschwanden & Kan, 1999b). For the set of gauged and ungauged catchments covered by the map, one would simply read off the low flow values from the map in an application case. For any other site, less rigid guidance is given by the procedure. Interpolation methods and additional hydrological reasoning are recommended as a starting point for obtaining low flow values at such sites.

Norway is currently in the process of establishing a national procedure for estimating low flows in small ungauged catchments (Engeland *et al*., 2006). The focus is on the "common low flow" (clf), *a derived minimum discharge closely correlated to* Q95. Engeland *et al*. (2006) compared a multiple regression approach between clf and catchment characteristics with gridded low flow estimates from a rainfall–runoff model in a region in southwest Norway and found that the regression approach was less biased. Engeland recommended that a low flow map be developed to be used as a national procedure, but the degree of subjective judgement involved in practical applications of the map has not yet been determined.

For the United States of America, the US Geological Survey has developed regional (state-by-state) multiple regression equations between low flow quantiles and catchment characteristics representing terrain, land cover, soil type, and precipitation (Ries, 2002). These regression equations are currently integrated in a Geographic

Information System (GIS) application known as StreamStats. The application will allow interactive delineation of catchment boundaries, catchment characteristics, and resulting flow characteristics. At the date of submission of this paper, the method has been implemented for the state of Idaho, and work is underway to implement it for several other states as well (http://water.usgs.gov/osw/programs/streamstats.html). Idaho was divided into eight regions by a cluster analysis of catchment characteristics, and separate equations were developed for each region (Hortness & Berenbrock, 2001). The procedure yields unique low flow estimates for ungauged catchments.

In New Zealand, a conceptual recession model of low flows has been developed, where the mean annual minimum flow is predicted as the consequence of a season-long period of alternating typical events and recessions. Some parameters of the model were estimated from climate data (which are available for the whole country), some by global calibration of a parameter for all sites, and others by at-site calibration in combination with a regionalisation method for 92 hydrologically uniform regions. Using all these parameters, estimates of mean annual minimum flow were made for all ungauged streams in New Zealand (Henderson *et al*., 2004, 2005).

Although regressions with catchment characteristics are used in most countries, the other aspects of the estimation procedures differ significantly. In Austria, so far, no national procedure has been available for estimating low flows in both gauged and ungauged catchments. In this paper, we present such a national low flow estimation procedure. The estimation strategy will follow two main goals, (1) to make best possible use of available data, and (2) to include the assessment of model uncertainty in the estimates. For the first goal, a number of comparative studies had been carried out previously, to find the best performing method for a specific data situation, i.e. long records (Laaha, 2000), short records (Laaha & Blöschl, 2005), and sites without records (Laaha & Blöschl, 2006a,b). In this paper, possible combinations of these methods are assessed in order to find a technique that makes best use of the available data. For the second goal, uncertainty assessment, the propagation of errors, including measurement errors of Q95 values of long (20-year) and short (5–19-year) records and prediction errors of multiple regression, is represented by an error model. The error model is based on analyses of the measurement errors of Q95 of the standard period as a consequence of rating errors (Laaha, 2000), and on errors of Q95 from short records compared to Q95 from the standard period that are related to climate variability (Laaha & Blöschl, 2005). We will use this assessment of uncertainty to estimate lower and upper confidence limits of low flows, rather than deriving a single low flow estimate for each catchment.

## HYDROLOGICAL SETTING AND DATA

### Study area and regional low flow processes

Austria covers an area of 84 000 km$^2$ and is climatically, physiographically and hydrologically, highly diverse. In the lowland east, low flows mainly occur in the summer and are a result of evaporation exceeding precipitation, which depletes the soil moisture stores of the catchments. In the Alpine areas in the west of Austria, low flows mainly occur in the winter and are a result of snow storage and frost processes.

Precipitation strongly affects low flows. Annual precipitation ranges from 500 mm in the east to about 2800 mm in the west. Potential evaporation has an inverse pattern ranging from 730 mm year$^{-1}$ to about 200 mm year$^{-1}$. Geology and soil types also exhibit a rich variety within Austria—crystalline rocks, limestone, and Flysch in the mountains; Quaternary sediments in the Alpine valleys; and marine basins filled with Quaternary and Tertiary sediments in the lowlands. Typically, hard rock aquifers exist in the mountains, and porous aquifers in the valleys and part of the lowland. These modulate the climate controls giving rise to an enormous spatial complexity of low flows in Austria.

## Discharge data, disaggregation and catchment selection

Discharge data used in this study are daily discharge series from 603 stream gauges. Nested catchments were split into sub-catchments between subsequent stream gauges. The advantages of using sub-catchments over using complete catchments are that they facilitate the regionalisation to small ungauged catchments and decrease the spatial statistical dependence of the low flow data. However, the errors may be somewhat larger, as the low flow characteristics are estimated from differences of the streamflow records at two gauges. Two sets of sub-catchments were used in this study. The first set consists of 325 sub-catchments between stream gauges which have been continuously monitored during the period 1977–1996. To increase the number of streamflow records, a second data set consisting of 481 sub-catchments was used that included shorter records of at least 5 years. This data set covers about 60% of the national territory of Austria. In compiling these data sets only those stream gauges were included for which low flows were not significantly affected by anthropogenic impacts (Laaha & Blöschl, 2003). The low flow data sets hence represent an almost natural low flow regime.

## Low flow characteristic

The low flow estimation procedure presented in this paper focuses on the Q95 flow quantile [Pr($Q$ > Q95) = 0.95], i.e. the discharge that is exceeded 95% of the time. This low flow characteristic is widely used in Europe and has been chosen because of its relevance for numerous water resources management applications (see, e.g. Kresser *et al*., 1985; Gustard *et al*., 1992; Smakhtin, 2001). For the study area, Q95 is closely correlated with the mean annual minimum flow, but is more robust to data errors (Laaha *et al*., 2005b). For stream gauges without an upstream gauge, the Q95 low flow quantile was calculated directly from the streamflow data. For stream gauges with an upstream gauge, the Q95 of the sub-catchment was estimated as the difference of the Q95 values of the two gauges. This is a more robust estimator than the quantile of the differential hydrographs but does need the assumption of synchronicity of low flows. Given the long time scale of low flows in Austria, this is likely a good approximation. All Q95 low flow values were standardised by (sub)-catchment area to obtain specific low flows q95 (L s$^{-1}$ km$^{-2}$) used in the subsequent analyses. Figure 1 shows the specific low flows so obtained. The largest values occur in the high precipitation areas in the

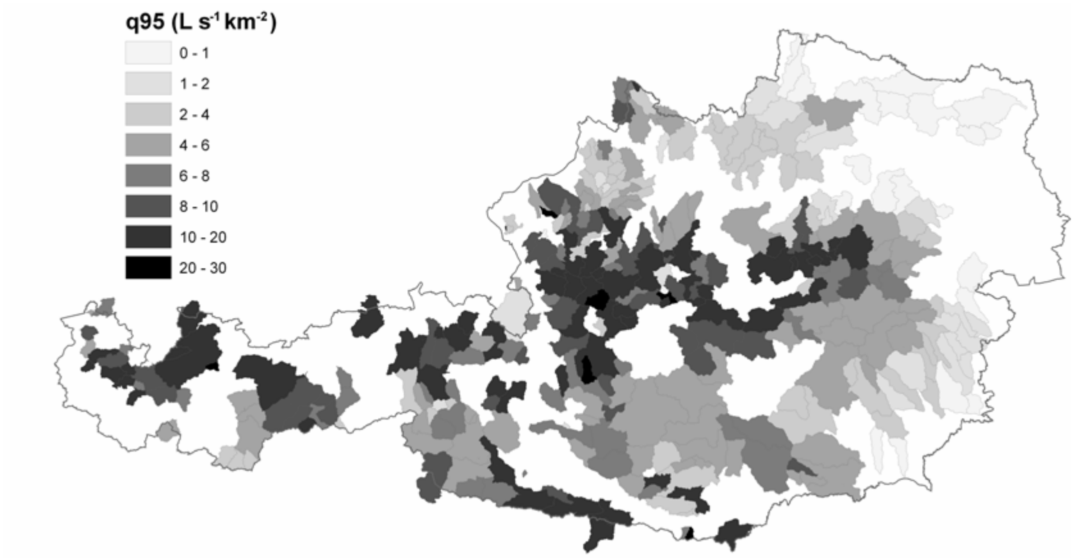


**Fig. 1** Specific low flow discharge q95 (L $s^{-1}$ $km^{-2}$) from runoff data observed in 325 sub-catchments in Austria. Alpine catchments show higher values and a larger variability.

Alps, with typical values ranging from 6 to 20 L $s^{-1}$ $km^{-2}$. The lowest values occur in the east ranging from 0 to 8 L $s^{-1}$ $km^{-2}$, although the spatial pattern is much more intricate.

## Catchment characteristics

We examined 31 physiographic catchment characteristics $X$ for low flow regionalisation in this paper. They relate to sub-catchment area ($A$, $10^1$ $km^2$), topographic elevation ($H$), topographic slope ($S$), precipitation ($P$), geology ($G$), land use ($L$), and stream network density ($D$, $10^2$ m $km^{-2}$). Topographic elevation is represented by the altitude of the stream gauge ($H_0$, $10^2$ m), maximum altitude ($H_+$, $10^2$ m), range of altitude ($H_R$, $10^2$ m) and mean altitude ($H_M$, $10^2$ m). Topographic slope ($S$) is represented by the mean slope ($S_M$, %), and by area percentages of slight (<5°) slope ($S_{SL}$, %), moderate (5–20°) slope ($S_{MO}$, %), and steep (≥20°) slope ($S_{ST}$, %). Precipitation is represented by average annual precipitation ($P$, $10^2$ mm), average summer precipitation ($P_S$, $10^2$ mm), and average winter precipitation ($P_W$, $10^2$ mm). Geology ($G$) is represented by the area percentages of Bohemian Massif ($G_B$, %), Quaternary sediments ($G_Q$, %), Tertiary sediments ($G_T$, %), Flysch ($G_F$, %), limestone ($G_L$, %), crystalline rock ($G_C$, %), shallow groundwater table ($G_{GS}$, %), deep groundwater table ($G_{GD}$, %), and source region ($G_{SO}$, %). Land use ($L$) is represented by the area percentages of urban ($L_U$, %), agriculture ($L_A$, %), permanent crop ($L_C$, %), grassland ($L_G$, %), forest ($L_F$, %), wasteland—rocks ($L_R$, %), wetland ($L_{WE}$, %), water surfaces ($L_{WA}$, %), and glacier ($L_{GL}$, %). All characteristics were first compiled on a regular grid and then combined with the boundaries of 21 000 topographic sub-catchments to obtain their catchment characteristics (Laaha & Blöschl, 2006b). The average area of the sub-catchments is about 4 $km^2$, and the maximum area is 281 $km^2$. These sub-catchments are a full tessellation of Austria.

## ESTIMATION STRATEGY

Most national low flow estimation procedures are based on regressions between the low flow characteristics and catchment characteristics (e.g. Vogel & Kroll, 1992; Gustard *et al*., 1992; Schreiber & Demuth, 1997; Skop & Loaiciga, 1998). If the study domain is heterogeneous in terms of the low flow processes, the domain is usually split into regions and the regressions are applied to each region independently (e.g. Gustard & Irving, 1994; Clausen & Pearson, 1995). We adopt this regional regression approach, as Austria is hydrologically very diverse. There are, however, numerous other aspects in which the national estimation procedures differ, e.g. the identification of regions. The procedures differ because of differences in the hydrological processes driving low flows, because of differences in data availability, and perhaps also as a result of familiarity with a particular method. For the case of Austria, it has not been clear from the start what method is the most suitable. Because of this, the following general approach was adopted: For each of the steps of the estimation procedure, several alternative methods were compared. The relative performance of the alternative methods was then tested on the Austrian data set. Whenever possible, this test consisted of leave-one-out cross-validation where one withholds the streamflow data of a particular station, makes an estimate for that location and then compares the estimate with the streamflow data, repeating the procedure for all stations. This fully emulates the ungauged catchment case. The advantage of cross-validation over other techniques of assessing estimation accuracy is its robustness and its ability to evaluate the performance of the methods even if the assumptions underlying the methods are far from valid (Efron & Tibshirani, 1993). For each step, the method with the smallest cross-validation error was then adopted as part of the national low flow estimation procedure. Process reasoning was invoked whenever possible. For example, the seasonal occurrence of low flows was used as an indicator of the processes driving low flows. This is of particular importance in Austria where low flow generating processes differ vastly in different parts of the country.

To maximise the accuracy of the estimates, we combined relevant sources of information depending on data availability. Most importantly, the catchments differ in terms of their availability of streamflow records. There are three main cases: (a) catchments where long streamflow records are available (1977–1996) – for these, the low flow estimates will be the most accurate, and accuracy chiefly depends on the measurement accuracy of discharge; (b) catchments where short streamflow records are available – here, the accuracy of the estimates depends on the record length and some adjustment is needed to account for the particular time window of the measurements; and (c) catchments without streamflow records – for these catchments some type of regionalisation method is needed to estimate low flows from catchment characteristics. The estimates of the three catchment cases are then finally combined by a spatial adjustment method to exploit the streamflow information of nested catchments. A schematic of the overall procedure is shown in Fig. 2.

National low flow estimation methods also differ in the degree of judgement that is exercised in the application of the procedure. At one end of the spectrum are maps of the entire country from which one simply reads off the low flow value at the site of interest. In this type of procedure any person would arrive at the same low flow estimate for a particular site. At the other end of the spectrum are recommended

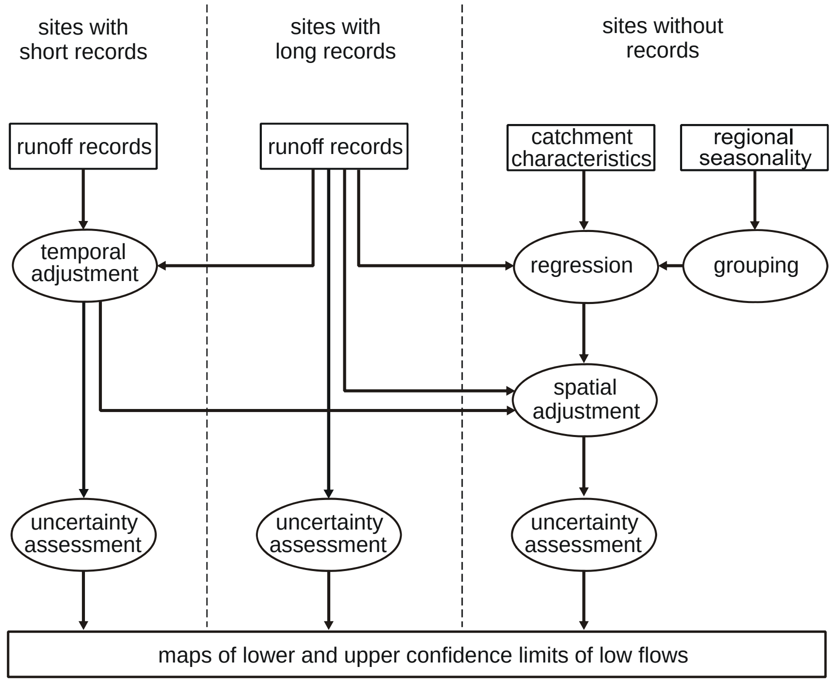


**Fig. 2** Low flow estimation strategy for Austria, combining methods for sites with short streamflow records, long streamflow records and without streamflow records, i.e. ungauged sites.

methods that use local data not provided by the national procedure. A compromise consists of procedures that do provide all the data, but where some choice needs to be made by the user. For example, this may involve decisions on which stations to include in the analysis. Clearly, the advantage of the latter methods is that they allow one to incorporate local knowledge on low flow processes. However, this comes at the expense of an element of subjectivity. For the case of Austria, the approach adopted is to produce a map of low flow values with explicit uncertainties attached to them. Rather than plotting a single low flow value for a particular catchment, we plot a lower and upper confidence limit to represent a range of likely low flow estimates. In the application case, local information and hydrological reasoning can be used to judge what a suitable low flow estimate would be for a particular site of interest given the range provided by the procedure. The following sections present the components of the low flow estimation procedure.

## GAUGED SITES

### Reference period

The interest of using characteristic low flow values usually resides in representing the long-term average behaviour of low flows, commensurate with the life time of a structure or the design period of a management measure. Due to climatic variability and other sources of variability, low flow characteristics estimated from a few years of streamflow data deviate from the long-term average. Because of this, it is usually recommended to use streamflow records of 20 years or more for low flow estimation

(DVWK, 1983; Tallaksen & van Lanen, 2004). Hence, for a single site, low flow characteristics are usually calculated from the entire record that is available. In a regional context, available record lengths will differ, so choice of a standard observation period is useful to make the low flow characteristics at different sites comparable. In this study, a standard observation period of 20 years, between 1977 and 1996, was chosen. This period represents a trade-off between number of gauges and record length (Laaha, 2002). Additionally, gauges with shorter records have been used which, however, need to be adjusted for climate variability.

## Temporal adjustment

A number of climate adjustment methods exist for inferring the long-term low flow characteristics from short records. The basic idea is that information on the local specifics of the low flow regime at the site of interest (termed subject site) is combined with information about how the short record at the subject site fits into the long-term picture by making use of a longer record at a donor site.

Following the general strategy of developing the low flow estimation procedure, we compared a number of adjustment methods based on the Austrian data set (Laaha & Blöschl, 2005). The climate adjustment methods consist of two steps: donor site selection and record augmentation. The donor site selection methods examined are the downstream site, catchment similarity and correlation methods. The accuracy of the methods was assessed by comparing the adjusted estimates from hypothetically shortened records with estimates from the full 20-year record at the same site. The results indicate that the downstream donor selection method performs best on all

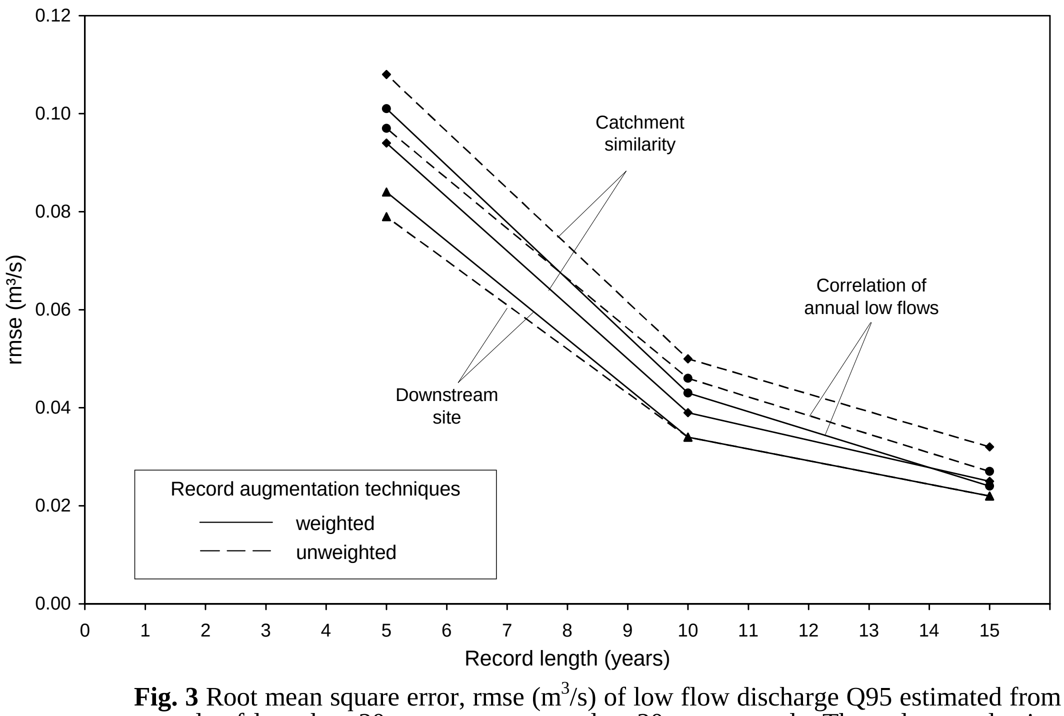


**Fig. 3** Root mean square error, rmse ($m^3$/s) of low flow discharge Q95 estimated from records of less than 20 years as compared to 20-year records. Three donor selection techniques are combined with two record augmentation methods.

scores (Fig. 3). Using this method, low flow characteristics from 5-year records explain 95% of the variance of those of the 20-year observation period, with a root mean square error (rmse) of 0.08 $m^3/s$, i.e. only 10% of the average Q95 value. These errors are larger than the measurement errors of the standard period, with a rmse of about 3% of the average Q95 value (Laaha, 2000), but smaller than the errors of a regression model, with rmse between 12 and 44% of the average Q95 value, depending on the region (Laaha & Blöschl, 2006a). The downstream donor selection method was hence used in this study for climate adjustments of low flow characteristics from short (5–19 years) records. For the record augmentation, an unweighted method was used as the analysis indicated that it produced slightly more accurate results than an alternative, weighted method (Fig. 3). The low flow characteristics at the subject sites were then adjusted by:

$$QS_{pred} = QS_0 \left( \frac{QD}{QD_0} \right) \tag{1}$$

where $QS_{pred}$ is the adjusted value of Q95 at the subject site, $QS_0$ is Q95 at the subject site calculated from the overlap period, $QD_0$ is Q95 at the donor site calculated from the overlap period and QD is Q95 at the donor site calculated from the entire observation period (see Kroiß *et al.*, 1996; Laaha & Blöschl, 2005). When no downstream gauge was available, the next upstream gauge was used as a donor site.

## UNGAUGED SITES

### Catchment grouping

For the regional regression approach, regions need to be identified that are homogenous so that the same regression equation can be expected to apply to all catchments within a region. In some instances it is clear how to group catchments into regions, but, more often, the choice is far from obvious. Several methods have been proposed in the literature. In order to find the best catchment grouping method for the study area, four methods were compared in terms of their performance in predicting low flows for ungauged catchments (Laaha & Blöschl, 2006a). These are the residual pattern approach (e.g. Hayes, 1992; Aschwanden & Kan, 1999a), weighted cluster analysis (Nathan & McMahon, 1990), regression trees (Breiman *et al.*, 1984; Laaha, 2002), and regions of similar low flow seasonality (Laaha & Blöschl, 2006b). All of these methods use low flow data and most of them use catchment characteristics as well. For each group, a regression model between catchment characteristics and q95 was fitted independently. The performance of the methods is assessed by leave-one-out cross-validation of the regression estimates which emulates the case of ungauged catchments. Results indicated that the grouping based on seasonality regions performs best (Fig. 4). It explains 70% of the spatial variance of q95. The favourable performance of this grouping method is likely related to the striking differences in seasonal low flow processes in the study domain. The regression tree grouping performs second best (explained variance of 64%) and the performance of the residual pattern approach is similar (explained variance of 63%). The weighted cluster analysis only explains 59% of the spatial variance of q95 which is only a minor improvement over the global

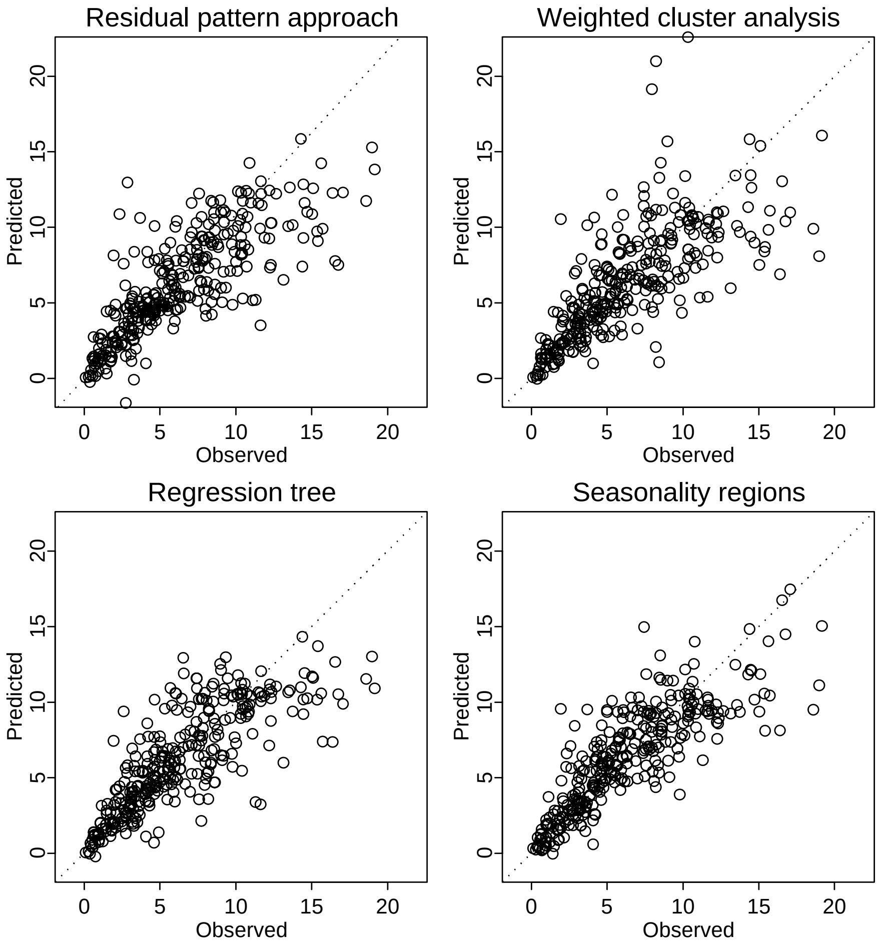


**Fig. 4** Scatter plots of predicted *vs* observed specific low flow discharges q95 (L $s^{-1}$ $km^{-2}$) in the cross-validation mode. Each panel corresponds to one grouping method and each point corresponds to one catchment.

regression model, i.e. without using any grouping (explained variance of 57%). An analysis of the distribution of estimates of all methods suggests that, again, the grouping method based on the seasonality regions has the most favourable characteristics, although all methods tend to underestimate specific low flow discharges in the very wet catchments (Fig. 4). Seasonality-based regions were therefore used in this study for catchment grouping, and a classification tree was used to allocate ungauged catchments to one of the groups according to catchment characteristics (Laaha & Blöschl, 2006a).

## Regression model

As mentioned above, specific low flow discharge q95 was related to catchment characteristics by multiple regression. To minimise intercorrelations and multicollinearity, a stepwise regression approach was adopted and Mallow's Cp (Weisberg, 1985, p. 216) was used as the criterion of optimality. Cp is a penalised selection criterion which takes the gain of explained variance as well as the parsimony of models into account and yields models that are optimal in terms of prediction errors.

Fitting regression models in hydrology is often complicated by single extreme values or outliers. Eliminating outliers may improve the goodness-of-fit, but this does not necessarily entail an increase in the predictive power of the model. However, extreme values may act as leverage points and force the fitted model close to them, particularly if the regression model is fitted by the least squares method, which increases the magnitude of the residuals of the remaining points. We therefore adopted an iterative robust regression technique in this study. Initial models were fitted by stepwise regression and then checked for leverage points using Cook's distance (e.g. Weisberg, 1985). These leverage points were removed from the sample and the regression model was refitted iteratively until no leverage points remained. The final model quality was assessed for all data including leverage points. q95 was used in all regional regressions without transformation, as exploratory analyses of the data suggested that transformations did not increase the predictive performance.

The resulting regional regression models are shown in Table 1. The regions are those of Laaha & Blöschl (2006b), with the sole modification that two regions, Lower Carinthia and the Alpine region, have been combined here, since the original regression estimates were too high for some parts of Lower Carinthia that are not well represented by low flow measurements. The regression model performs well in most regions, with coefficients of determination ranging from 60 to 70%. The regression model for the Pre-Alps of Styria exhibits a larger coefficient of determination of 89%. It appears that the seasonality characteristics contain a lot of information highly relevant to low flow regionalisation. The exception is the Alpine, winter low flow dominated region, where the coefficient of determination is only 51%. This low coefficient of determination may be related to lumping three types of seasonality (A, B, C) that do not form contiguous regions into a single contiguous region. Closer inspection of the results indicated that the model performs quite well in the valleys, but exhibits some bias at altitudes above 1800 m a.s.l. This was because high-altitude catchments were under-represented in the calibration data set. In a more detailed study focusing on the Alpine region, a stepwise multiple regression model for 105 catchments with mean altitude >1800 m a.s.l. was therefore fitted using supplemental catchments of hydropower plants in the Tauern region (Laaha *et al*., 2005a). For this additional component model, the coefficient of determination was found as 68%, which is a significant improvement over the original value of 51%. For catchments between 1200

**Table 1** Component regressions of specific low flows q95 (L $s^{-1}$ $km^{-2}$) in Austria.

| Group | Region | $R^2$ | Model: $\hat{q}_{95}$ = |
|---|---|---|---|
| A–C | Alps < 1200 m | 51% | $0.67 + 0.40P + 0.17G_Q - 0.01G_C + 6.43L_{WE} + 0.14S_M - 0.04L_R - 0.20H_0$ |
| A–C | High Alps > 1800 m | 68% | $-8.21 + 2.64P + 0.74H_M - 0.02G_C - 0.12P{\cdot}H_M$ |
| D | Pre-Alps (Styria) | 89% | $-7.99 + 1.08P + 0.04L_F$ |
| E | Pre-Alps (Vorarlberg) | 60% | $18.20 - 0.18S_{MO}$ |
| 1 | Flatland and hilly terrain (N, E of Austria) | 71% | $-0.12 + 0.11S_M + 0.05G_{GS} + 0.02G_C$ |
| 2 | Bohemian Massif | 64% | $-3.31 + 1.96P_W$ |
| 3 | Foothills of Alps (Upper Austria) | 68% | $-10.04 - 0.76D + 3.27P - 2.22H_0$ |
| 4 | Flysch zone | 63% | $-6.17 + 0.06G_L + 2.07P_S - 0.06L_F$ |

and 1800 m mean altitude, the predictions of the original model and the high-altitude model were linearly combined according to altitude.

## Spatial adjustment

The regression equations were now applied to all 21 000 sub-catchments. The specific low flow discharges so estimated are termed $q95_i$, and the corresponding low flows $Q95_i$. They represent the low flows between two nodes of the stream network, or local low flows. Because of the residual errors of the regression, the sum of the predicted low flows, $Q95_i$, within a gauged catchment *g* will generally differ from the observed low flow of that catchment, $Q95_g$. As the latter is the more accurate low flow estimate, a spatial adjustment of the $q95_i$ was introduced. Following the general philosophy of the low flow estimation procedure, we compared two adjustment methods. In the first method, termed adjustment of residual catchments, we adjusted the $q95_i$ by the differences of observed low flows of subsequent gauges by:

$$q95'_i = \frac{Q95_g - \sum_h Q95_h}{\sum q95_i A_i} \cdot q95_i \tag{2}$$

where $Q95_g$ is the low flow observed at gauge *g*, $Q95_h$ is the low flow observed at upstream neighbour gauge *h*, *i* is the sub-catchment located upstream of gauge *g* but downstream of gauge *h*, and $A_i$ is the catchment area. If the catchment area of gauge *g*, $A_g$, and the sum of the areas of the upstream neighbours *h*, $\sum A_h$, differ too much, the adjustment may become inaccurate. We have therefore only adjusted those catchments *i* for which $A_g \le 9 \cdot \sum A_h$. For the remaining catchments, we set $q95'_i = q95_i$. In the second method, termed adjustment of total catchments, we scaled the $q95_i$ by the ratio of the sum of all $Q95_i$ upstream of gauge *g* and $Q95_g$.

We examined two additional cases without spatial adjustment: The third method was as above, but without adjustment, i.e. $q95'_i = q95_i$. In the fourth method, we applied the regression equation to the total catchments rather than the sub-catchments. This means that for any node on the stream network, the flow of the total upstream area was considered as opposed to the flow between two nodes as in the other cases. For comparison, the sub-catchment low flows $q95'_i$ from methods 1–3 were aggregated to total catchment low flows for all gauged catchments. All four estimates were then compared to the observed low flows at the gauges in a cross-validation mode, i.e. without using the particular gauge for adjustment against which the estimates were tested.

The results of the cross-validation are shown in Fig. 5 in terms of the error distribution for all gauged catchments. Root mean square errors have been estimated, both in terms of specific discharges and in terms of discharges. The rmse of the first and second methods are 1.85 L $s^{-1}$ $km^{-2}$ (or 0.165 $m^3$/s) and 1.89 L $s^{-1}$ $km^{-2}$ (or 0.181 $m^3$/s), respectively. This means that the adjustment of residual catchments performs slightly better. The third and fourth methods give rmse of 2.06 L $s^{-1}$ $km^{-2}$ or (0.210 $m^3$/s) and 2.07 L $s^{-1}$ $km^{-2}$ (or 0.216 $m^3$/s), respectively. These means that whether one applies the regression equations to sub-catchments or total catchments does not change the results

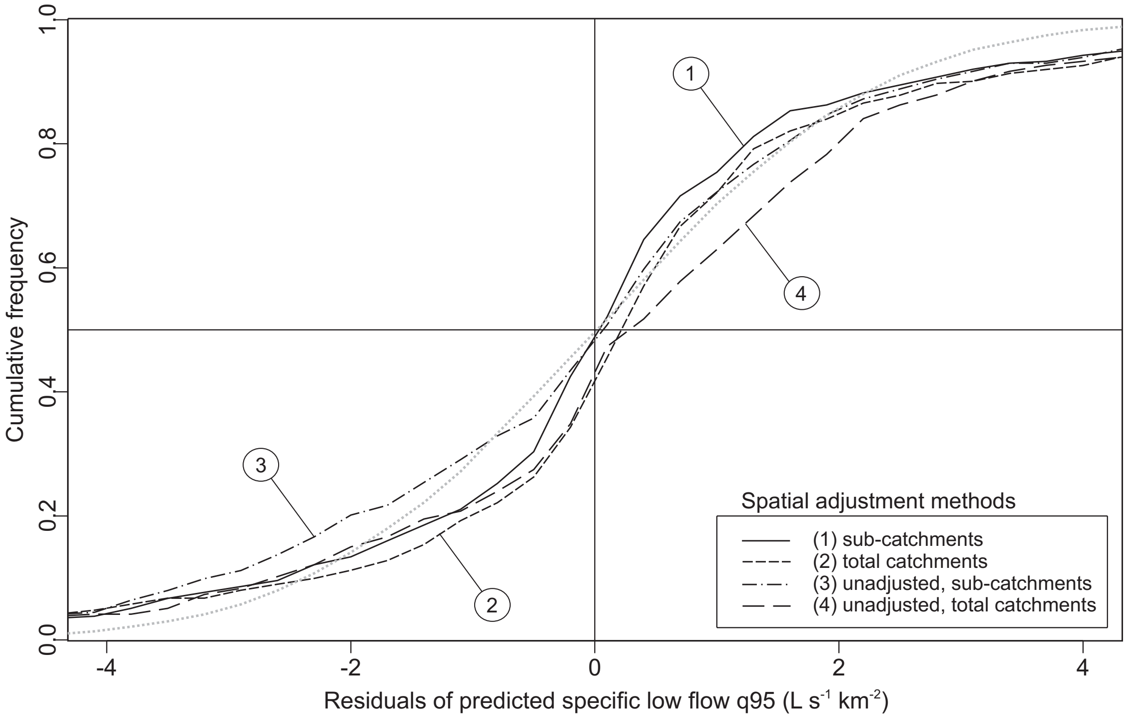


**Fig. 5** Cross-validation performance of four spatial adjustment methods: 1: regression of sub-catchments, adjustment of residual catchments, aggregation; 2: regression of sub-catchments, adjustment of total catchments, aggregation; 3: regression of sub-catchments, no adjustment, aggregation; and 4: regression of total catchments, no adjustment. A normal distribution (*N*[0, 1.85]) is shown for comparison (grey dotted line).

much but the adjusted estimates are better than the unadjusted ones. All rmse values were estimated without using the 5% outliers. These outliers can be explained by karst effects or seepage and are hence not genuinely attributable to regionalisation errors. Figure 5, however, does include these outliers. The error distributions of each method (black lines) are plotted along with a normal distribution using the moments of the best method for comparison, i.e. $N[0, 1.85]$. The error distribution indicates that the methods that are based on total catchments (second and fourth method) are slightly biased and tend to overestimate low flows. The first method of adjustment of residual catchments is the best and was therefore chosen for the national procedure.

## UNCERTAINTY ASSESSMENT

### Confidence limits

In a national procedure it is useful to have an understanding of the uncertainties associated with the low flow estimates. We therefore evaluated confidence limits of the estimated low flows:

$$\mathrm{q95_{lo}} = \mathrm{q95'_i} - e \qquad \mathrm{q95_{up}} = \mathrm{q95'_i} + e \tag{3}$$

where $\mathrm{q95_{lo}}$ and $\mathrm{q95_{up}}$ are the lower and upper confidence limits (L s$^{-1}$ km$^{-2}$), respectively, and $e$ (L s$^{-1}$ km$^{-2}$) is the standard deviation of errors, here termed the prediction error. Assuming normally distributed errors, the probability that the true specific low flow lies between the confidence limits is 68%. The magnitude of the prediction error *e* for sub-catchment *i* depends on whether a spatial adjustment of the low flows has been made or not (equation (2)).

## Error of spatially unadjusted prediction

For sub-catchments where low flows are estimated by the multiple regression model without spatial adjustment to local observations, the prediction error *e* is the regression standard error $e_1$ of predicting individual observations:

$$e = e_1 = \sqrt{s^2 + \mathrm{se}^2\left(\hat{\mathrm{q}}95_0\right)} \tag{4}$$

which consists of two components: *s* is the standard deviation of the residuals of multiple regression, and $\mathrm{se}(\hat{\mathrm{q}}95_0)$ is the standard error of the predicted mean value $\hat{\mathrm{q}}95_0$ for catchments with catchment characteristics $X_0$ (Draper & Smith, 1998, p. 80). The term *s* is constant within each region and is shown in Table 2. However, $\mathrm{se}(\hat{\mathrm{q}}95_0)$ depends on the catchment characteristics and for regressions based on a single predictor, it can be calculated as:

$$\mathrm{se}\left(\hat{\mathrm{q}}95_0\right) = s\left\{\frac{1}{n} + \frac{\left(X_0 - \overline{X}\right)^2}{\sum\left(X_j - \overline{X}\right)^2}\right\}^{1/2} \tag{5}$$

where *n* is the number of catchments used for model calibration, $X_0$ is the catchment characteristic of the sub-catchment of interest, $\overline{X}$ is the mean of the catchment characteristics in the region, and $X_j$ are the characteristics of catchments *j* used for model calibration. For multiple regressions, as used here, equation (5) is replaced by a matrix equation (Draper & Smith, 1998, p. 130) which has been evaluated for all sub-catchments.

**Table 2** Group mean q95 and standard deviation of residuals *s* (both in L $s^{-1}$ $km^{-2}$) of the component regression models.

| Group | Region | Mean | *s* |
|---|---|---|---|
| A–C | Alps < 1200 m | 8.18 | 2.61 |
| A–C | High Alps > 1800 m | 5.41 | 1.77 |
| D | Pre-Alps (Styria) | 3.61 | 0.42 |
| E | Pre-Alps (Vorarlberg) | 8.71 | 1.65 |
| 1 | Flatland and hilly terrain (N, E of Austria) | 1.29 | 0.57 |
| 2 | Bohemian Massif | 3.33 | 1.12 |
| 3 | Foothills of Alps (Upper Austria) | 4.81 | 1.07 |
| 4 | Flysch zone | 6.61 | 2.81 |

## Error of spatially adjusted prediction

The prediction errors *e* of sub-catchments that were spatially adjusted tend to be smaller than those of the unadjusted sub-catchments. They were approximated by the weighted average of error $e_1$ and an error $e_2$ related to the locally observed low flows:

$$e = \alpha \cdot e_1 + (1-\alpha) \cdot e_2 \quad (6)$$

The weighting factor $\alpha$ was set to 0.5 for the study area based on sensitivity analyses. $e_2$ was calculated from error propagation:

$$e_2 = \sqrt{e_g^{\,2} + \sum_h e_h^{\,2}} \quad (7)$$

where $e_g$ and $e_h$ are the standard deviations of the errors of the observed low flows Q95 at the downstream and upstream gauges, respectively (L $s^{-1}$ $km^{-2}$). For gauges with the full 20-year standard period, they were set to the measurement errors $e_{g,m}$ and $e_{h,m}$ which were evaluated by Laaha (2000) as 3% of the Q95 discharge. For gauges with shorter records, $e_g$ includes an additional component due to climate variability $e_{g,s}$:

$$e_g = \sqrt{e_{g,m}^{\,2} + e_{g,s}^{\,2}} \quad (8)$$

The expression for $e_h$ is analogous; $e_{g,s}$ was estimated from the analyses of short records presented earlier and ranged from 4% to 24% of the Q95 discharge for 15- to 5-year streamflow records. From this assessment, the catchments and sub-catchments used for spatial adjustment exhibit errors between 3% and 47%. The distribution of errors is strongly skewed (95% of the (sub)catchments exhibit errors less than 25%), so the median error is only 5.8%.

To illustrate the uncertainty of the low flow estimates, Fig. 6 shows the errors of both the spatially unadjusted and adjusted catchments. Each marker relates to one catchment, so the sum of the number of markers in Fig. 6(a) and (b) is equal to the total number of catchments in the Austrian data set. The figures indicate that the errors of the spatially adjusted catchments (Fig. 6(b)) tend to be smaller than those of the

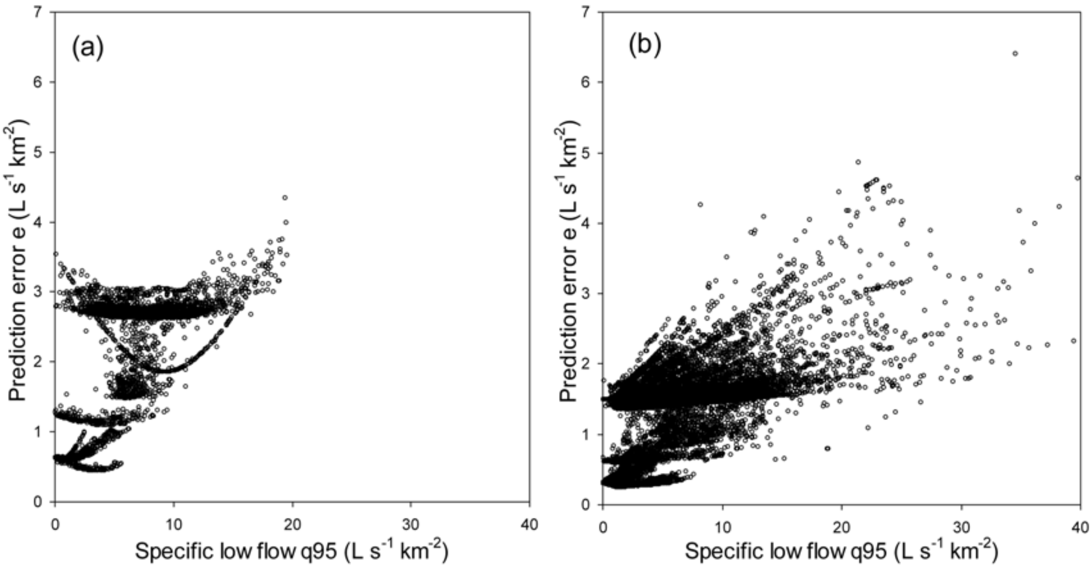


**Fig. 6** Uncertainty of low flow estimates in terms of prediction errors $e$ (L $s^{-1}$ $km^{-2}$) plotted against discharge $q95'_i$ (L $s^{-1}$ $km^{-2}$) for 21 000 sub-catchments: (a) prediction errors $e$ of spatially unadjusted catchments (equation (4)); and (b) prediction errors $e$ of spatially adjusted catchments (equation (6)).

unadjusted catchments (Fig. 6(a)). The main purpose of the adjustment is to reduce the uncertainty in low flow estimation, so one would expect smaller errors for the adjusted catchments. However, for the catchments in Fig. 6(a) no suitable stream gauges were available, so no adjustment was possible. It is interesting that Fig. 6(a) shows hyperbolic patterns, each of which corresponds to one component regression models for a region. These patterns reflect the dependence of the prediction errors on the values of the predictor variables (equation (5)), i.e. catchments with extreme catchment characteristics exhibit higher prediction errors than those with average characteristics. In Fig. 6(b), these hyperbolic patterns are no longer apparent because of the adjustment. It is also interesting that the range of the adjusted specific low flows (Fig. 6(b)) is larger than that of the unadjusted low flows (Fig. 6(a)). The regression model tends to reduce spatial variability but some of this smoothing is compensated by the adjustment to locally observed streamflow.

## SUMMARY OF AUSTRIAN PROCEDURE

We present a procedure for estimating Q95 low flows in both gauged and ungauged catchments, where Q95 is the flow that is exceeded 95% of the time. For each of the steps of the estimation procedure, several alternative methods were tested on the Austrian data set by leave-one-out cross-validation, and the method that performed best was used in the procedure. To maximise the accuracy of the estimates we combined relevant sources of information, including long streamflow records, short streamflow records, and catchment characteristics, according to data availability. Rather than deriving a single low flow estimate for each catchment, we estimated lower and upper confidence limits to allow local information to be incorporated in a practical application of the procedure. The procedure consists of the following steps:

(a) *Temporal (climate) adjustments for short record lengths*
We used streamflow data from a reference period of 1977–1996, but did include shorter records. These were adjusted by the longer streamflow records from donor catchments. An adjustment technique that uses one adjacent gauge at the same river as a donor was chosen here as it performed better than alternative adjustment techniques.

(b) *Grouping catchments into eight seasonality based regions*
For sites where no streamflow data are available, low flows were estimated by a regional regression model which uses separate multiple regressions between specific low flows and catchment characteristics for individual regions. The catchments were grouped into eight regions based on low flow seasonality, as this method performed better than alternative groupings. The seasonality represents the main low flow driving processes such as winter snow processes and summer soil moisture deficit.

(c) *Regional regressions of low flows with catchment characteristics*
The multiple regression model was calibrated independently to each of the eight seasonality regions. One of the regions was subdivided based on catchment altitude to represent the high Alpine catchments. The regression equations have been found by stepwise regression to maximise robustness and predictive power, and minimise collinearity. 325 sub-catchments with 20-year streamflow records were used for the

calibration. The regression model was then applied to 21 000 sub-catchments that give a full tessellation of Austria.

(d) *Spatial adjustments for exploiting local streamflow data*
To reduce the estimation error of the regression model, local streamflow data were used, wherever available, to adjust the regression estimates. An adjustment technique (termed adjustment of residual catchments) that uses the differences of streamflow data of neighbouring gauges was chosen here as it performed better than alternative adjustment techniques. If the neighbouring stream gauges were far apart, however, the sub-catchments were not adjusted.

(e) *Uncertainty assessment*
In a final step, the prediction errors of the low flows were estimated. For catchments without spatial adjustment, the prediction error is the regression standard error of predicting individual observations. For catchments that were spatially adjusted, the prediction error was approximated by the weighted average of this regression standard error and an error related to the locally observed low flows. The upper and lower confidence limits of the low flow estimates were found by the estimate plus/minus the prediction error. If the errors are normally distributed, the probability that the true specific low flow lies between the confidence limits is 68%.

The resulting maps of lower and upper confidence limits of low flow discharges for the 21 000 sub-catchments in Austria are shown in Fig. 7. Note that only those stream gauges were included in the data set for which low flows were not significantly affected by anthropogenic impacts. The estimates hence represent a near-natural low flow regime. The general low flow pattern is similar to the rainfall regime with the high precipitation areas exhibiting higher low flows. There are, however, important smaller scale patterns. High alpine areas exhibit much smaller specific low flows (q95 $< 4$ L $s^{-1}$ $km^{-2}$), which is related to snow pack storage and freezing processes. The eastern part of Austria exhibits very small low flow values (q95 $< 1$ L $s^{-1}$ $km^{-2}$), which is due to the high evaporation rate in summer and low rainfall.

The low flow estimates will be published in the *Hydrological Atlas of Austria* to be made available to a wider audience. In a practical application, one would aggregate the sub-catchment low flows for the site of interest. As the *Atlas* includes an electronic version and contains an aggregation tool, this is straightforward. The aggregation tool identifies sub-catchments of a site of interest by their hierarchical identification code, and calculates the upper and lower limit of low flows of the catchment of interest by the area-weighted average of the upper and lower limits of the sub-catchments. The resulting confidence bounds are exact if the low flows of the sub-catchments were perfectly correlated. As, in reality, the correlation will likely be large but not unity, the estimates of the aggregated confidence intervals will be slightly too large and hence “on the safe side”. For gauged catchments, where local Q95 values are available from the runoff records, the aggregated Q95 estimates are fully consistent with the local Q95 values. The estimated confidence intervals, however, are somewhat larger than the measurement error as they are estimated as a linear combination of measurement errors and regionalisation errors (equation (6)). The regionalisation error component accounts for potential uncertainties due to anthropogenic effects not captured in the original data. If no anthropogenic effects exist in a particular catchment, it is recom-

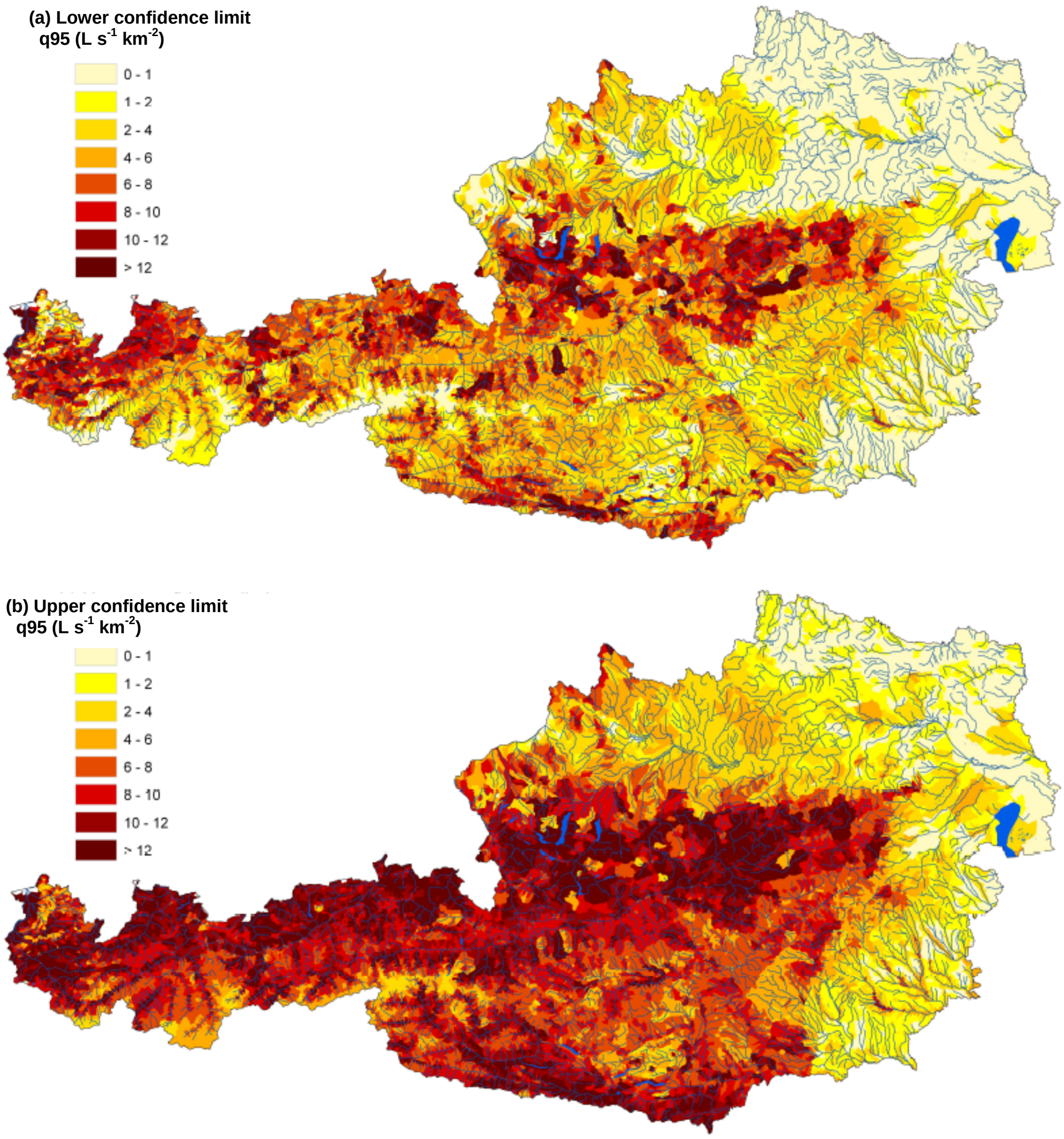


**Fig. 7** Confidence bounds of specific low flows q95 (L $s^{-1}$ $km^{-2}$) in Austria (equation (3)): (a) lower limit, and (b) upper limit.

mended to use the Q95 values obtained from the local runoff record instead of the aggregated regionalised values.

For the application case, we then recommend to consult local information before choosing the Q95 low flow value for the site of interest. The local information and hydrological reasoning should be used to judge what a suitable low flow estimate would be for a particular site of interest, given the range provided by the aggregation of Fig. 7. Local information may be acquired during site visits to get an appreciation of the hydrological peculiarities of the area of interest. Blöschl (2005) illustrated how qualitative information obtained during site visits can be profitably used in hydrological assessments.

As compared to other national low flow procedures, the Austrian scheme is a compromise in the degree of judgement needed. Some national procedures consist of maps of the entire country from which one simply reads off the low flow value at the site of interest. This is simple and non-ambiguous and does not involve any judgement. Other procedures consist of recommended methods without providing the basic data. This allows one to incorporate local data in a flexible way and usually involves a considerable amount of judgement by the analyst. In the Austrian case, we have chosen to provide confidence limits. For some applications, such as large-scale, aggregate assessments, these may suffice as reasonable guesses of the low flow conditions. For more local applications, it is prudent to include local information. We think that local information is important for maximising the accuracy of the low flow estimates. This is both because of the enormous hydrological variability in space and the experience that local knowledge is often available and can indeed improve regional estimates. Providing the regional information as confidence limits rather than as a single value facilitates the merging of these two sources of information in a consistent way. Hence, by the method presented here, we believe to have combined the merits of both philosophies of regional low flow estimation.

**Acknowledgements** Analyses are based on data provided by the Geological Survey of Austria; the Austrian Federal Ministry of Agriculture, Forestry, Environment and Water Management; and the Austrian Hydrographic Service. Many thanks to all members of the NE-FRIEND Low Flow Group for providing a valuable forum for low flow and drought research. The paper is dedicated to the late Prof. Harald Strelec, head of the Department of Applied Statistics and Computing.

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**Received 28 June 2006; accepted 22 January 2007**