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Chapter 7

Prediction of flow duration curves in ungauged basins

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7.1 For how long do we have water?

A wide variety of approaches have been adopted to quantify runoff variability, with differing degrees of emphasis on high flows (floods), low flows, seasonal variation of flows, and annual flows, and many of these are discussed in other chapters of this book. An additional feature of runoff variability that has considerable practical relevance is the period of time runoff remains higher than a specified magnitude, otherwise known as "flow duration". The flow duration curve (FDC), which is the subject of this chapter, is a graphical representation of the frequency, or the fraction of time (hence the word, duration) during which a specified magnitude of runoff is equalled or exceeded. Representation of the entire runoff hydrograph time series (typically daily runoff, but it can also be hourly, or even monthly) in the form of the FDC makes the latter a compact signature of runoff variability, and a valuable tool to diagnose rainfall-runoff responses in gauged catchments at a holistic level, and to regionalize them to ungauged catchments. However, by representing runoff variability in the frequency domain as the FDC, information on the timing of the runoff response is lost. This is reflected in the basin's runoff seasonal flow regime (Chapter 6), and of course, in the complete runoff hydrograph (see Chapter 10).

FDCs (for daily runoff) can be constructed empirically for gauged sites by (1) ranking observed runoff in ascending order and (2) plotting each ordered observation versus its corresponding duration (e.g. in days), or its fractional duration (which is dimensionless). Comparisons of FDCs between catchments of different sizes or in different climatic regions can be assisted by expressing the FDC in terms of normalized runoff (normalized by drainage area or by mean annual runoff). If a stronger emphasis is needed to be given to either the low flow or flood portion of the FDC, then it can be plotted semi-logarithmically, expressing the logarithm of runoff as a function of (fractional) duration.

The FDC can be constructed for the entire runoff record presenting a long-term representation of the runoff regime, or as an ensemble of annual FDCs (AFDCs) estimated for each year of record (Vogel and Fennessey, 1994, 1995). Together, these offer a perspective of the between-year, or inter-annual, variability of the FDCs, which can be considerable in some locations, and enable the estimation of the mean or median of the AFDCs as well as the variances or confidence intervals of the runoff quantiles. The mean or median AFDC is a hypothetical AFDC, which describes the annual runoff regime for a typical hydrological year. Normally the median AFDC is preferred to the mean AFDC because it is less sensitive to the presence of abnormally wet or dry years in the observed runoff time series (Vogel and Fennessey, 1994). Figure 7.1 presents an example of the construction of the long-term FDC, and the ensemble of AFDCs based on daily runoff record of the Kamp River taken at Zwettl in Austria.

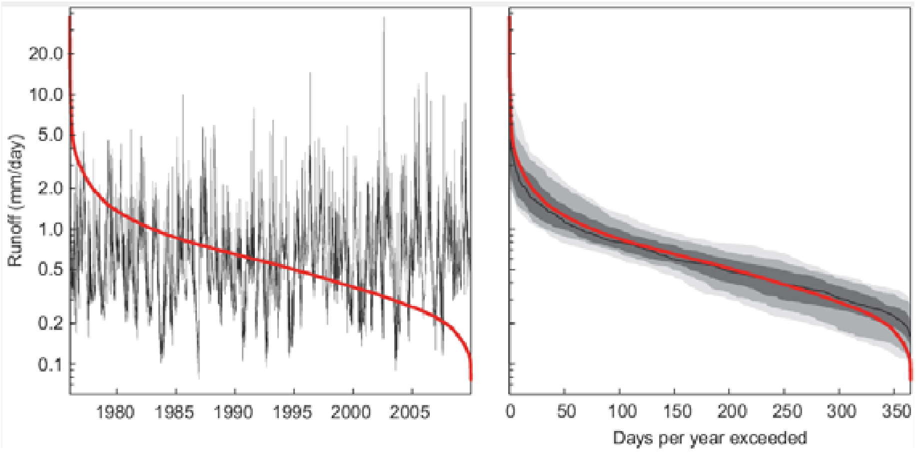

Figure 7.1 Definition of flow duration curves: Left: Daily hydrograph based on measured daily runoff of Kamp River at Zwettl in Austria, juxtaposed against the long term (period-of-record) flow duration curve (red line). Right: quantiles of the annual flow duration curves, with long-term FDC (red line).

Because of its ability to condense a wealth of information about runoff variability into a single graphic image, and because of the relevance of runoff variability to both human water use and the maintenance of environmental health, the FDC is used in a wide range of applications (Vogel and Fennessey, 1995). The FDC can help quantify the ability and reliability of a river to meet demand for water by humans (for municipal and industrial uses, irrigated agriculture), and has been the basis for the design of small reservoirs or schemes for water uptake from rivers (Dingman, 1981; McMahon, 1993). FDCs are heavily used in the design and operation of hydropower schemes, for maximising hydropower production. Increasingly, as humans interfere with the runoff of the river for hydropower production or through extractions for domestic and industrial consumption, the downstream environment tends to suffer. FDCs are increasingly used to determine and set environmental flow standards to protect the aquatic habitat and maintain and restore ecosystem health (Poff et al., 1997; Olden and Poff, 2003). For example, the U.S. Fish and Wildlife Service (Milhous et. al., 1990) use FDCs for determining the suitability of river corridors as ecological habitats. FDCs are also used to determine the optimum allocation of water for different human uses, and for the environment (Alaouze, 1991), and for the purpose of evaluating the impact of alterations in flow regimes. In this respect, Vogel et al. (2007) introduced the concepts of eco-deficit and eco-surplus, both indicators estimated based on the FDC.

Figure 7.2 presents two different applications of the FDC, the first one for setting design standards for environmental flows (left) and the second for hydropower production (right). Both involve the construction of appropriate water resource indices, relating to habitat conditions or hydropower potential respectively, through the combination of the FDC with a rating curve for the index of interest (Vogel and Fennessey, 1995; Bonta and Cleland, 2003). Figure 7.2 (left) illustrates the construction of two habitat duration curves, one for the natural scenario (blue) and the other for a control scenario which accounts for water extractions upstream (red). The water resource index in this case is the total habitat area (weighted useable area, WUA). The rating curve that connects WUA to runoff, which can be derived via simulation based on ecological considerations is shown (Milhous et al., 1990). The construction of a power duration curve is also shown (Figure 7.2, right), highlighting the within-year variability of the amount of hydroelectric power that can be produced. Once again, a key component in this construction is the relationship between hydropower and runoff, which are the design characteristics of a particular type of hydropower scheme.

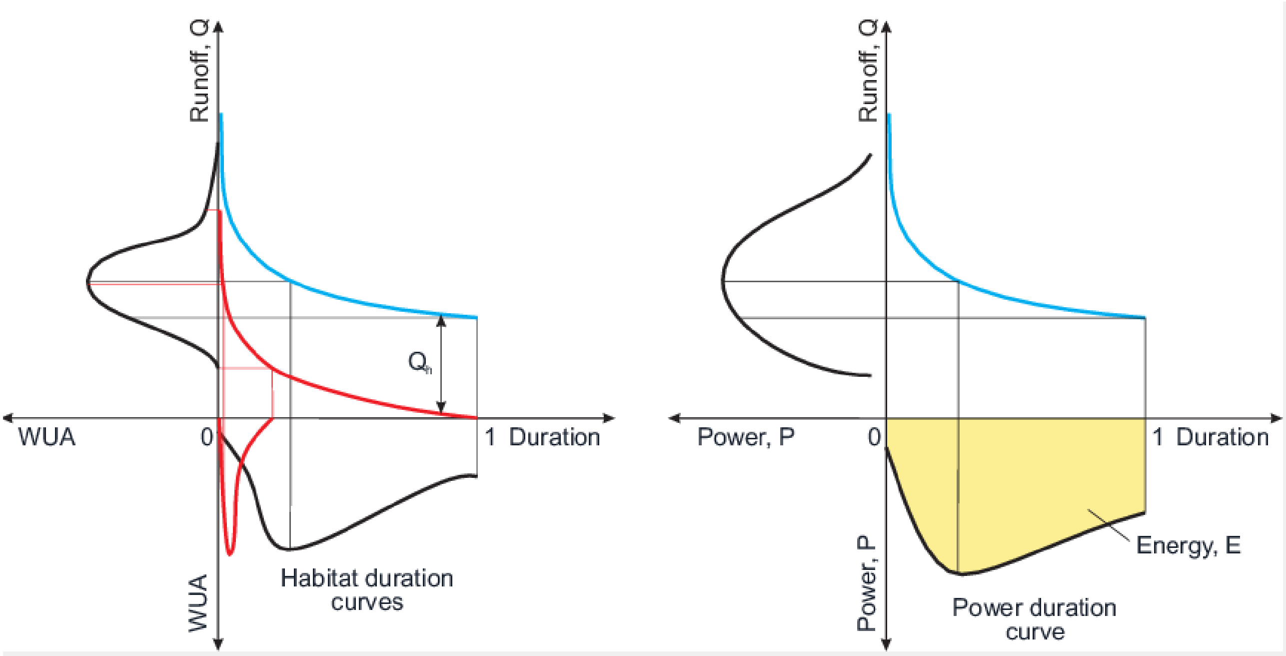

Figure 7.2 – Two illustrations of the utilization of flow duration curves (FDCs): Left: construction of two habitat duration curves from FDCs and a rating curve for Weighted Useable Area (WUA), an indicator of habitat suitability for specified wildlife species, the higher the value the higher the suitability; the two habitat (WUA) duration curves are for the natural scenario (blue line) and for an altered scenario characterized by upstream human abstraction Q_h (red line); Right: construction of the power-duration curve based on typical power-runoff relationship (area under the power-duration curve is a measure of the hydroelectric power that may be produced over the period of interest).

Finally, since the FDCs are a key signature of runoff variability, they can also be used for evaluating rainfall-runoff model output and for calibrating such models (e.g., Fennessey, 1994; Westerberg et al. 2011), for filling gaps and extending daily runoff time series, and when a regional FDC model is available, for generating runoff series in ungauged river basins (Chapter 10). FDCs can also be used to define low flows and perform low flow frequency analyses (Chapter 8).

7.2. Flow duration curves: processes and similarity

Figure 7.3 presents illustrative examples of two FDCs for comparative analysis. The FDCs have been plotted for two catchments of similar size, but located in contrasting hydrological regions, one in Northern Italy and the other in New Mexico, USA. The FDCs indicate that the catchment in New Mexico is not only ephemeral, but also has significant inter-annual (between-year) variability, a normal characteristic for ephemeral catchments. On the other hand, the catchment in Northern Italy is perennial, but with very little inter-annual variability. It is clear that the FDCs for each catchment are very different and this section aims to address why they are so different. For predictions in ungauged basins it is essential to understand what factors cause FDCs to vary between catchments. The notion of hydrologic similarity in the context of FDCs helps us to group similar catchments together. Understanding of the climatic and landscape (catchment) controls on the FDCs can enable the extrapolation of empirical FDCs derived from gauged catchments to ungauged catchments within a similar or homogeneous region. Likewise, understanding of the process controls of the observed FDCs helps not only to delineate homogeneous regions but also to use appropriate process models to extrapolate/reconstruct FDCs in ungauged basins.

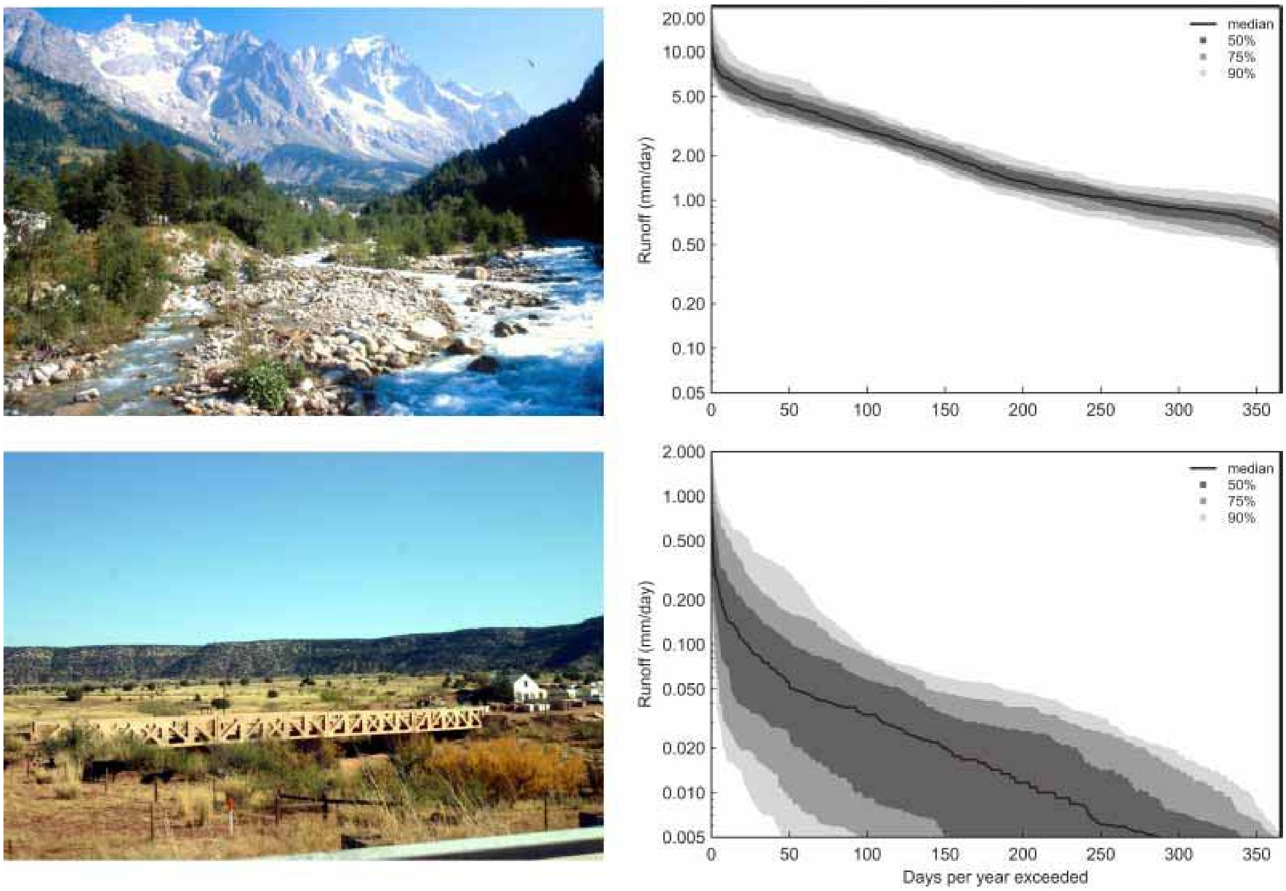

Figure 7.3: Median and between-year variability of flow duration curves. Top: Dora Baltea at Tavagnasco, Italy (area 3311 km^2, mean annual precipitation 949 mm); Bottom: Mora near Shoemaker, New Mexico, USA (area 2859 km^2, mean annual precipitation 483 mm). Photos: XX, K.Ahler.

This section first discusses the process controls responsible for the shapes of flow duration curves, and how these are governed by the combination of climate, and catchment characteristics. This understanding is then used to formulate a list of similarity indices that can be used to group similar catchments, and to develop relationships to extrapolate FDCs from ungauged to gauged catchments in hydrologically similar (i.e., homogeneous) regions.

7.2.1 Processes

Overview: The flow-duration curve (FDC) represents a distillation of the within-year, or intra-annual, variability of runoff, presented in the frequency domain. The FDC arises from the interplay of climate regime, catchment size and morphology, vegetation cover, and the properties of the subsurface domain, which together control the various runoff components. The shape of the FDC is therefore governed by both precipitation variability and how water moves through the catchment. Deciphering the controls of both climate processes (e.g., precipitation, temperature, radiation or potential evaporation) and catchment characteristics (i.e., soil, topography, vegetation type and functioning, catchment size, human impacts) on the shape of FDCs is the key to their prediction in ungauged basins.

As the major climate control on the FDC of a river basin is precipitation, one can expect signatures of precipitation variability to be reflected, to varying degrees, in the runoff variability of a catchment. For example, in a region of high flows the shape of the FDC may closely resemble the statistics of precipitation due to the dominance of fast flow processes, whereas for intermediate flows the dominant control may be represented by soil water storage and its partitioning into evaporation and slow flows. On the other hand, low flows could be governed, in the absence of precipitation, by the competition between deep groundwater flows and riparian evaporation (see Chapter 4).

Figure 7.4 presents two illustrative examples, both based on numerical simulations, which demonstrate that different parts of the FDC can be governed by different process controls. Figure 7.4 (top panel) presents model predicted partitioning of total hillslope runoff according to whether it relates to slow matrix flow (slow and even water movement through the subsurface), and both rapid and slow preferential flow (uneven water movement often through wormholes, cracks etc.) (Beckers and Alila, 2004), and their representation in the corresponding FDCs. Yokoo and Sivapalan (2011) carried out independent work on the basis of which they postulated that the FDC can be partitioned into three distinct parts, each of which is governed by different mechanisms or process controls (Figure 7.4, bottom panel): (i) the upper part, which represent high flows, is governed by flood processes for which the dominant control is the interaction of extreme rainfall and fast runoff processes; (ii) the middle part, relates to the mean runoff and its seasonality, for which the dominant control is the competition and seasonal interaction between available water, energy and storage (see Section 5.2.1); and (iii) the lower part, is governed by base flow recession behaviour over dry periods for which the dominant control is the competition between deep drainage and riparian zone evaporation.

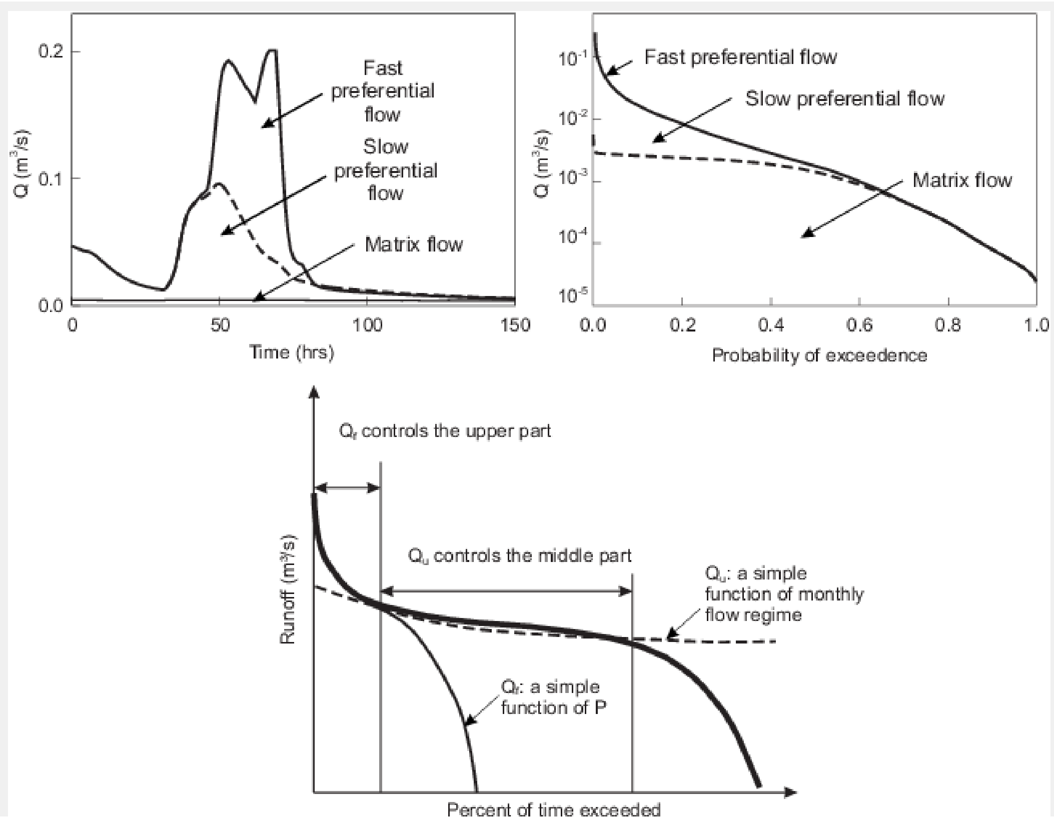

Figure 7.4. Illustration of process controls of different parts of the FDC: Top panel (left): model-predicted contributions of matrix flow and hillslope preferential flow, fast and slow, to runoff at hillslope scale for a single flood event; Top panel (right): contributions of model predicted matrix flow and preferential flows (fast and slow) to the FDC for a given water year (Beckers and Alila, 2004). Bottom panel: schematic diagram illustrating the understanding gained through model simulations regarding the shapes of the FDCs and controls on the different parts of the FDC based on the partitioning of total runoff into fast (Q_f) and slow (Q_u) flows (Yaeger et al., 2012, and Yokoo and Sivapalan, 2011).

The changing process controls can be recognized in the FDCs presented in Figure 7.3. For example, the headwaters of the alpine catchment in Northern Italy (top panel) are characterised by the presence of glaciers. Glacial melting leads to maximum flows in summer, which due to the type of geology contributes to significant groundwater recharge in summer and releases substantial amounts of water to the river in winter as well. The presence of glaciers, and of snow processes in general, is the reason for the low between-year variability in the annual flow duration curves because the seasonal energy input is very stable on an annual time scale. The high base flow results because of the summer groundwater recharge, reflected in the flatness of the curve. In contrast, the catchment in New Mexico (bottom panel) has a semi-arid climate (with mean annual precipitation below 500 mm). The FDC mainly reflects precipitation variability (both within-year and between-year), the dominance of mostly surface and near surface fast flow processes, and the absence of substantial subsurface storage which would, if present, contribute delayed flows. These factors result in a FDC which, on average is ephemeral and therefore characterised by steeper slope than the mountainous Italian catchment.

Climate forcing: Climate impacts the FDC in several ways. The annual mean of the FDC (or the annual runoff) is governed by the aridity of the climate, as measured by the ratio of annual potential evaporation to precipitation, E_p/P), which reflects the competition between water and energy availability (as shown in Chapter 5: annual runoff). The slope of the FDC in the middle part of the curve, which is related to the variance of daily runoff, can be affected by the competition between the seasonality of precipitation and that of potential evaporation (including whether they are in-phase or out-of-phase), as mediated by subsurface drainage. Additional aspects of climate that can impact the FDC include the amount and timing of precipitation as snowfall, the eventual melting of accumulated snow, and also seasonal and spatial variations of vegetation cover and functioning (i.e., phenology), which affect the amount and timing of evaporation, and therefore the amount and timing of runoff (see Chapter 6.21). The seasonality of both snow processes and phenology can be attributed to the seasonal variations of air temperature (which is a climatic feature).

The net effect of these within-year interactions between climate seasonality and storage processes are clearly reflected in the seasonal flow regime (seasonal variability of runoff), which is the subject of study in Chapter 6. They can also manifest in the shape of the FDC, as shown in Figure 7.5, which presents several examples of both regime curves and FDCs from several catchments located across the continental United States. The results presented in Figure 7.5 show that the removal of the time element leads to the possibility that two catchments with different regime curves may yet have similar shapes of the FDCs, especially in humid catchments. For the catchment in Montana (MT) (Figure 7.5, red line) the peak in runoff caused by snowmelt is quite prominent, but for the rest of the year, runoff is relatively constant. This is manifested in the flat slope of the FDC, with a slight uptick at the low-probability end that includes the annual snowmelt events. Contrast this with the ephemeral, semi-arid catchment in North California (Noth Ca – black line) (Figure 7.5, green line), where the runoff varies a great deal throughout the year, manifested in a much steeper FDC overall, tending to zero runoff at 90% exceedance probability. Catchments with very different runoff coefficients have different FDCs, whereas catchments with very similar runoff coefficients have similar FDCs, as illustrated by two forested catchments in Pennsylvania (PA) and Virginia (VA) (Figure 7.5, blue and yellow line respectively). In both of these catchments the seasonal pattern of leaf-out in the spring and leaf-drop in the fall (i.e., indicators of phenology) are seen in the decrease in runoff from about May to October, even though the precipitation is fairly constant all year. The effect of phenology is less clear in the FDC, however, where the two catchments are nearly indistinguishable from one another and only slightly different from the Montana (MT) catchment. The results presented in Figure 7.5 highlight two key messages: one, that the seasonal flow regime (discussed in detail in Chapter 6) serves as the connective tissue between the high and low flow ends of the FDC, and two, due to the elimination of the timing of processes, catchments with different regime curves may yet give rise to similar shapes of the FDCs.

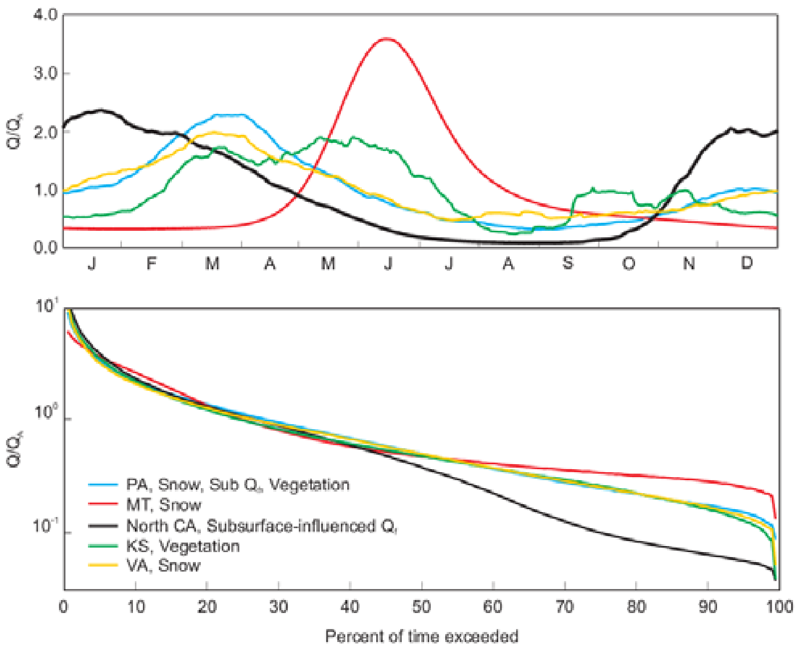

Figure 7.5. Smoothed seasonal flow regimes (using a 30-day moving window) (*top*), and long-term flow duration curves (*bottom*), based on 50-year record of observed daily runoff, normalized by mean annual daily runoff, from USA catchments located in Pennsylvania (PA), Montana (MT), Northern California (North CA), Kansas (KS), and Virginia (VA). From Yaeger et al., (2012).

Catchment characteristics: The within-year variability of runoff that is reflected in the FDC arises through runoff interaction with the within-year variability of climate forcing (precipitation, radiation and temperature, including seasonal vegetation dynamics), with the landscape, and the subsurface. The nature and extent of such filtering determines the shape of the FDCs. For example, catchments that are dominated by rapidly responding near-surface runoff processes will have steeper FDCs (with the possibility of high frequency of zero runoff) whereas catchments where slow processes dominate runoff generation may have less steep FDCs (see Figure 7.4). Key catchment characteristics that impact on the shape of the FDC include surface soil and vegetation characteristics that determine the partitioning of incoming precipitation into interception, infiltration and overland (fast) runoff. Water that infiltrates the soil is then partitioned into subsurface storage, subsurface (slow) drainage and evaporation through plant uptake and transpiration. These are all governed by geology through its impact on soil depth and soil permeability, vegetation cover and dynamics (with attendant impacts on root zone depth), and human induced land use and land cover changes.

Work over the past few decades has contributed to the accumulation of considerable empirical knowledge on the effects of these catchment characteristics upon the shape of FDCs. Musiake et al. (1975) investigated the effects of geology and climate type on the shape of FDCs in mountainous catchments in Japan. Ward and Robinson (1990) provided a summary of the effects of dominant soil types on FDCs in UK catchments. Fennessey and Vogel (1990) documented the important influence of catchment relief on the shape of FDCs. Burt and Swank (1992) investigated the effects of vegetation type on the FDCs. Figure 7.6 presents an illustration of the effect of geology on the shape of the FDCs for two catchments in the UK. The Eden at Penshurst is a rural catchment with scattered settlements developed on sands and clays, while the Test at Broadlands is underlain by permeable formations, 90% of which consist of chalk but with some tertiary deposits. The FDCs of the two catchments are very different. That of the Test is much flatter which is related to storage in the chalk aquifer and the close stream-aquifer interactions.

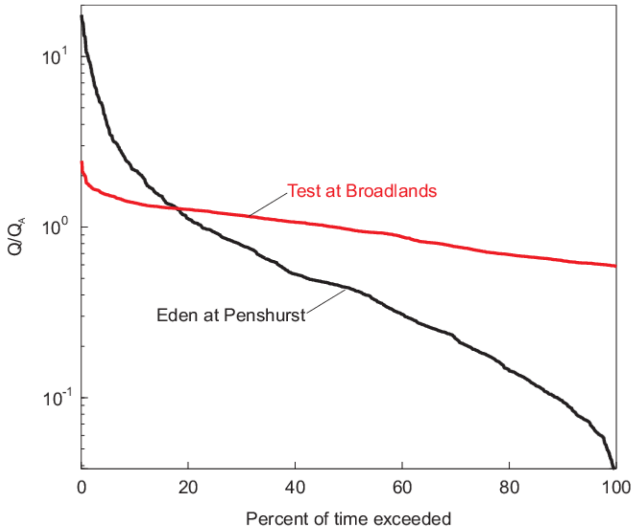

Figure 7.6 Flow-duration curves normalized by the mean runoff for the Eden at Penshurst, UK (area of 224 km², mean annual precipitation of 825 mm, clay dominated in the lower parts), and the River Test at Broadlands, UK (area of 1040 km², mean annual precipitation of 815 mm, chalk dominated catchment). Redrawn from Yadav et al. (2007).

Environmental Change: When extrapolating FDCs to ungauged basins it is important to recognise that the FDCs may be modified by environmental change, i.e., land-use changes, water abstractions, return flows, impoundments or climate change. In recent times, several experimental and empirical studies have been carried out to explore the effects of human-induced changes to the landscape, especially vegetation cover, on the FDCs. Brown et al. (2005) presented a review of Australian and New Zealand case studies on the impacts of changing vegetation cover. Figure 7.7 (top panel) depicts the FDC response to conversion of deep rooted native forest to shallow rooted pasture in the Wights catchment in south-western Western Australia, a relatively dry region where the annual actual evaporation of forests approaches annual precipitation. In this case, the replacement of native forest by pastures has led to a rapid rise of the groundwater table, and associated groundwater runoff (Schofield, 1996), resulting in large increases in low flows. On the other hand, Figure 7.7 (bottom panel) shows that reforestation has the opposite effect on the FDC. It presents the FDCs for the Red Hill catchment in Tumut, New South Wales, Australia, under one year and eight year old pines, indicating a 50% reduction in high flows and a 100% reduction in low flows with increasing age of the pines, with runoff in the low flow range ceasing once the pine plantation becomes well established (Vertessy, 2000).

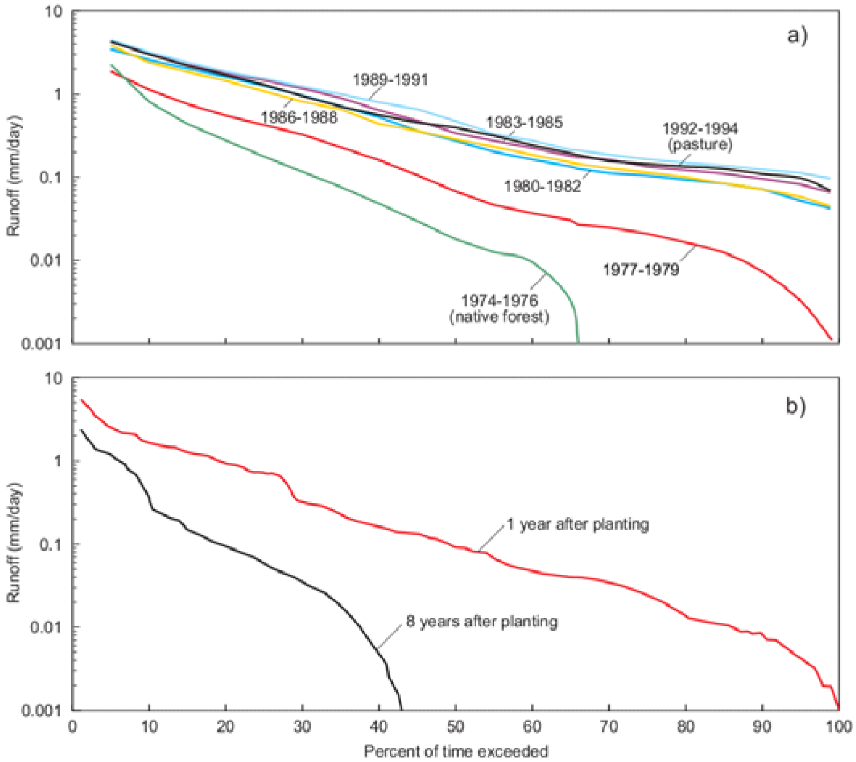

Figure 7.7 –(a) Response of flow-duration curves to conversion of native forest to pasture in the Wights catchment in south-west Western Australia. (b): Flow-duration curves for the Red Hill catchment, near Tumut, New South Wales, Australia showing considerable difference between one year old pines and eight year old pines. After Vertessy, (2000) and Brown et al., (2005).

Other kinds of anthropogenic impacts on the landscape can also exert a strong influence on the FDCs, such as water abstractions and construction of reservoirs (Brown et al., 2005; Smakhtin, 1999). Mu et al. (2007) analysed the effects of soil conservation measures (i.e., afforestation, creation of stable pastures, construction of terraces and sediment-trapping dams) on the FDCs for four different catchments located in the middle reaches of the Yellow River in China, characterized by semi-arid continental monsoon climate. They showed significant changes in normalized FDCs between the baseline (1957 – 1977) and treatment (1978 – 2003) periods, with three of the four study catchments showing significant reductions in runoff, especially in the range of low-flows. All these studies represent a fundamental wealth of knowledge that can assist in the identification of the dominant catchment processes that control the shape of the FDC under environmental change.

7.2.2. Similarity measures

Extrapolation and/or transfer of FDCs from gauged to ungauged catchments is critically dependent upon the notion of hydrologic similarity, i.e. what are the relevant physical (climatic and landscape) parameters that make two catchments similar. Understanding hydrologic similarity requires knowledge and understanding of the relationships between characteristics of the FDC (magnitude, shape etc.) and appropriate climatic and landscape characteristics.

Runoff similarity: Natural indices for assessing similarity among FDCs on the basis of runoff alone are the **slope** of the FDC or the **parameters** of probability distributions fitted to them. Examples of these similarity indices for a large number of catchments in the United States are presented in Figures 7.8 and 7.9. Figure 7.8 (left panel) presents a map of the ensemble average slope (over 50 years) of the middle limb of the FDC for catchments in Eastern USA based on the work of Sawicz et al. (2011). The slopes were estimated on the basis of the difference between 33% and 66%

quantiles of runoff for each year. The slope of the FDC in the middle part of the curve, which is related to the variance of daily runoff, is the result of the competition between the seasonality of precipitation and that of potential evaporation, and is mediated by subsurface drainage, thus providing a suitable synthetic similarity measure for the whole FDC.

On the other hand, Figure 7.8 (right panel) presents a linear interpolation of the catchment average slopes of the FDC based on the distances between the corresponding stream gauging stations. Clearly, this distance or proximity based measure of similarity is the default case, which can be substantially improved if the physical controls of the FDC are well understood. Understanding of such connections between the slopes of the FDCs and climate and/or catchment characteristics could provide a more advanced and hydrologically sound regionalization of the FDCs; this is illustrated in the next example.

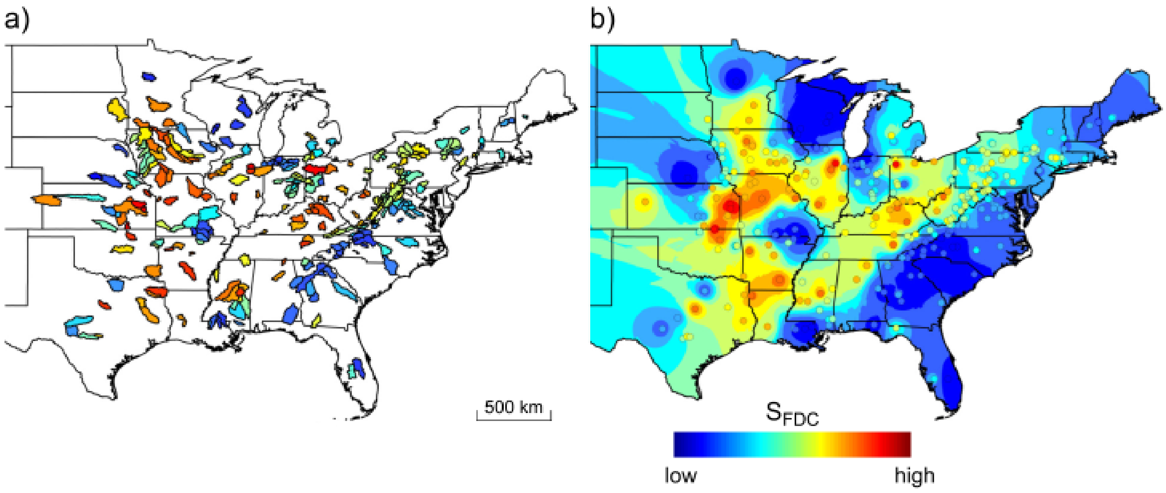

Figure 7.8. Slope of the flow duration curve for the Eastern USA using the data of Sawicz et al. (2011): (a) Catchment average values. (b) Linear interpolation between USGS gauging stations. In both cases, the colour is representative of the magnitude of the slope of the flow duration curve.

Cheng et al. (2012) carried out a comparative analysis of the FDCs for 197 catchments across the United States following the approach presented in Yokoo and Sivapalan (2011). They constructed FDCs for precipitation, fast (surface) runoff, slow (subsurface) runoff and total runoff, which they termed in this order PDC, FFDC, SFDC and TFDC and fitted a **three-parameter** truncated gamma distribution to each of these duration curves. For example, they fitted a three parameter mixed gamma distribution to scaled daily total runoff (scaled by mean daily runoff), which is given by:

$$f(q,\kappa,\theta,\alpha)=\begin{cases}\alpha, & q=0\\ (1-\alpha)\cdot g(q,\kappa,\theta), & q>0\end{cases} \tag{7.1}$$

where α is the probability of zero runoff, i.e., the number of zero runoff divided by the total number of runoff records; $g(\ )$ is probability distribution function of the gamma distribution; and κ and θ are parameters of gamma distribution, satisfying the condition that $\kappa\times\theta=1/(1-\alpha)$. This means that two of the three parameters, α, κ and θ and the mean daily runoff will be sufficient to characterize the duration curves. Cheng et al. (2012) found that the statistical model parameters showed interesting regional patterns. For example, Figure 7.9 presents the regional patterns of the shape parameter κ across continental United States. In each case these patterns also reveal how the shapes of the duration curves change from precipitation to fast flow, slow flow and total runoff, raising questions about the role of climate, catchment properties and the resulting process interactions.

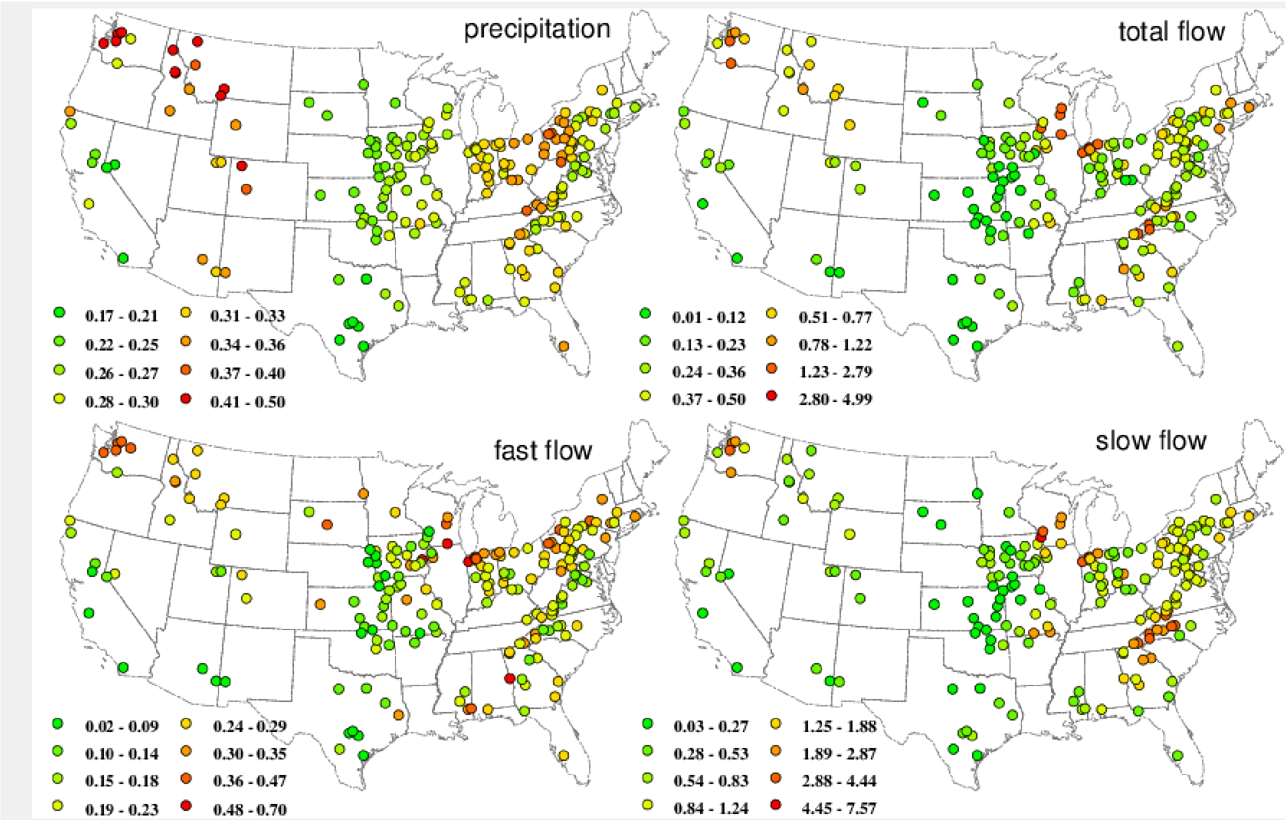

Figure 7.9 - Regional distribution of the shape parameter κ of the flow duration curves for 197 catchments across the continental United States (a) precipitation, (b) total runoff, (c) fast flow, and (d) slow flow. From Cheng et al., (2012).

Sauquet and Catalogne (2011) assessed hydrological similarity through two simple indicators: the concavity index (IC) and the seasonality ratio (SR). The concavity index is calculated as $IC = (Q_{10} - Q_{99})/(Q_1 - Q_{99})$ and measures the contrast between low-flow and high-flow regimes, representing the shape of the dimensionless FDC. Figure 7.10 represents the spatial distribution of the IC in France: values close to 1 are observed where large aquifers (e.g. in northern France) and storage in snow packs (e.g. in mountainous areas) moderate the variability of daily runoff. Values close to 0 are found in catchments exposed to contrasting climate (e.g. small catchments in the Mediterranean area experiencing hot and dry summers and intense short rainy events in autumn) and also to catchments with no storage capacity (e.g. founded on impermeable substratum) resulting in severe low-flow and quick runoff response to precipitation events. The seasonality ratio is the ratio of summer and winter median runoff. SR ≈ 1 applies to catchments with nearly uniform runoff throughout the year, often when significant groundwater contributions filter out seasonal climatic variability. Catchments influenced by snowmelt-fed processes display SR < 1, whereas this variable is above 1 for typical rainfall-fed catchments with low flow in summer and high flow in winter. The variation in SR is governed by geology and air temperature, and is consequently subject to topographic influences in France. Sauquet and Catalogne (2011) use IC and SR together to identify homogeneous regions in terms of the shape of FDC in France through different classification methods (see Section 7.2.3).

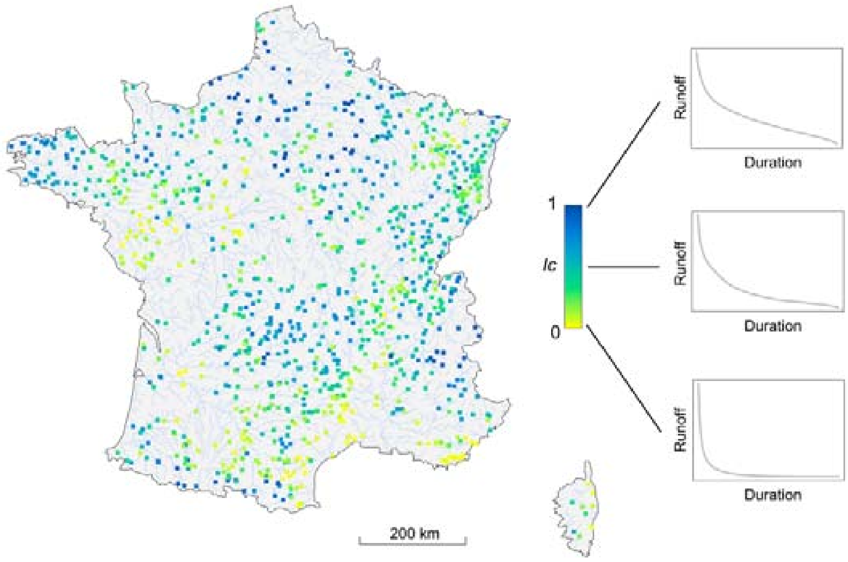

Figure 7.10. Concavity index IC observed at gauged catchments in France plotted on the location of their centre of gravity. From Sauquet and Catalogne, (2011).

In contrast to these studies, Ganora et al. (2009) defined a metric to quantify the differences as distances between FDCs and relate these distances to differences among catchments in terms of catchment and climatic characteristics. The main advantage of using distances between curves, rather than specific characteristics such as the slopes or model parameters, is that the entire curve is considered and not only their statistics/parameters. The method also allows one to compare the difference between FDCs with the differences between curves relating to climatic and catchment characteristics (e.g., information on the hypsometric curve can be used instead of the mean catchment elevation of the elevation range).

Climate similarity: Regionalization of FDCs works best if the daily runoff are normalized by the mean daily runoff. The mean daily runoff can be predicted, to first order, by the catchment's aridity index, which then becomes the primary indicator of catchment similarity. For example, Cheng et al. (2012) found a strong relationship between mean daily runoff and the aridity index, consistent with results presented in Chapter 5. Castellarin et al. (2007) show that the parameter representing the position of the FDC, which is linked to the mean annual runoff, is related to the mean annual net precipitation, along with the catchment area. Similar findings have been found by other studies (e.g., Viola et al., 2011; Li et al., 2010). Once the runoff is scaled by the mean daily runoff, the resulting annual FDCs are governed by several climatic and landscape characteristics that impact the transformation of the within-year variability of precipitation into the corresponding variability of runoff. The scale parameter used by Castellarin et al. (2007), which represents the within year variability of runoff, is correlated to the variability of the annual net precipitation. As per the framework provided by Yokoo and Sivapalan (2011), the first order control on the normalised FDC is the duration curve of precipitation (i.e., PDC, see Figures 7.4 and 7.9). This is especially true in the case of the FDC estimated for the fast flows (FFDC, see Figure 7.9). Cheng et al. (2012) derived a climatic index, $P_{max}\alpha_p$, based on the precipitation time series, and found that it had considerable explanatory power for FFDC, where P_{max} is the maximum daily precipitation and α_p is the probability of zero precipitation (i.e., fraction of non-rainy days within the year). As in the case of annual runoff (Sivapalan et al., 2011) the results of Cheng et al. (2012) also showed that there is a certain level of space-time symmetry, the variability of the FDCs between catchments being matched by their variability between years.

Other climatic controls on the shape of the FDC could be seasonality of precipitation and regional potential evaporation, including their relative magnitudes and phase difference. For example, Cheng et al. (2012) considered the value of the seasonality index, which represents a measure of within-year variability of precipitation, as a potential climatic index for the regional patterns of the FDC for slow flows (i.e., SFDC), although the relationship was not very strong.

Catchment similarity: The majority of the studies reported in the literature on the regionalization of FDCs have followed statistical approaches, in which case they attempt to relate quantitative measures of the FDCs (slope of the FDC, parameters of statistical distributions) to appropriate catchment characteristics. Catchment characteristics usually considered as potential indicators of the magnitude and shape of the FDCs are catchment size, vegetation cover (Ouarda et al., 2000) and surficial geology (e.g., Holmes et al., 2002; Castellarin et al., 2004a). Castellarin et al. (2007) found that the parameter representing the shape of the FDC depended on the overall catchment soil permeability. Sauquet and Catalogne (2011) found that the catchment yield and the percentage of impermeable substratum, both representing the effect of geology, controlled the slope of the FDC curve. They also found that the slope of the FDC decreased with increasing catchment size, and suggested that this may be due to increasing storage capacities, and the combinations of different river runoff patterns originating from upstream tributaries. Catchment area, percentage of permeable area, and areal average of the Curve Number (SCS-CN), along with mean annual precipitation, were found to be correlated with the shape of the FDC by Viola et al. (2011). Soil and geologic factors were statistically related to the shape of the FDC by several authors: Crocker et al. (2003, soil classes, baseflow index), Mahmoud (2008, available water capacity, soil depth, soil texture classes and baseflow index), Holmes et al. (2002, HOST soil classes, see Ch. 4), Claps and Fiorentino (1997, baseflow index) and Rianna et al. (2011, percentage of volcanic/carbonatic substratus). Li et al. (2010) found the Leaf Area Index to be related, together with the elevation difference, to the standard deviation of runoff, thus inversely proportional to the slope of the FDC: this may be due to their differential impacts on evaporation between summer and winter.

Despite this valuable work, the literature on process based approaches is still sparse. From a process perspective, the shape of the FDC (especially the middle part of the FDC, quantified by the slope of the FDC) can be influenced by the catchment's storage capacity (both surface and groundwater stores) and associated residence times (Lane and Lei, 1950), and how they interact with the seasonality of precipitation and potential evaporation. Without substantial storage from which to derive subsequent base flow, catchments will be characterized by steep FDCs and probably also experience a high frequency of zero runoff. Catchments with adequate storage to support base flow, on the other hand, will have FDCs with flatter slopes. This is usually also reflected in the magnitude of the baseflow index, the ratio of total volume of subsurface flow to precipitation on an annual time scale. This is confirmed by the work of Cheng et al. (2012) who found a significant relationship between the shape parameter of the FDC, κ, and the catchments' baseflow index (BI), as shown in Figure 7.11. Whereas Figure 7.11 (left) focuses on the variability between catchments, the results in Figure 7.11 (right) shows the nature of the variability between years for a subset of eight selected catchments, demonstrating considerable space-time symmetry in these relationships.

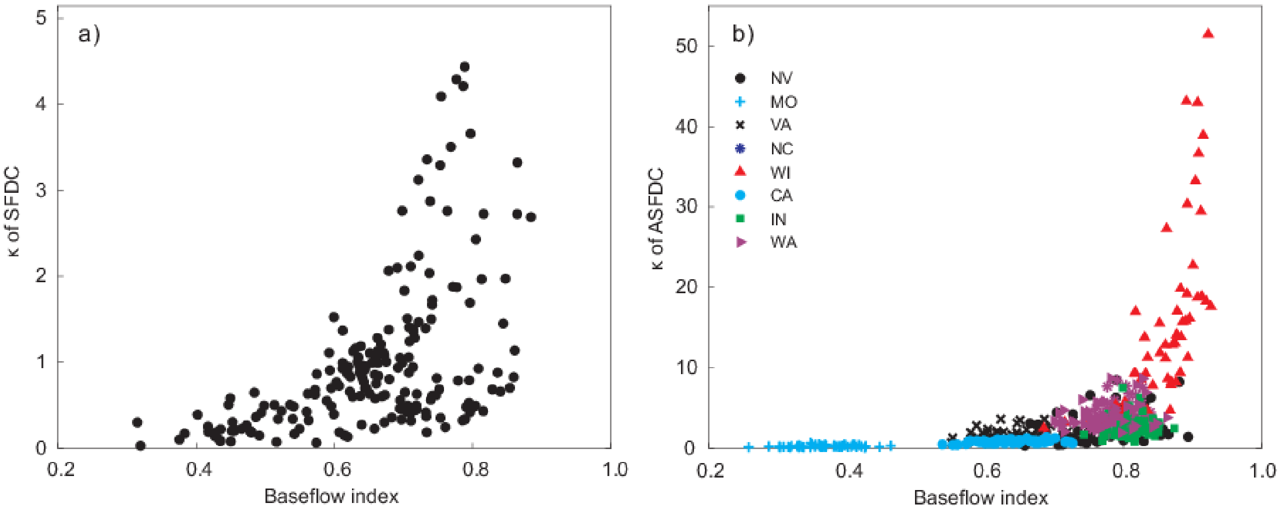

Figure 7.11. Relationship between the shape parameter κ (of the gamma distribution) of the SFDC (flow duration curve for slow flows) and the baseflow index for 197 catchments across continental United States: (a) variability between catchments using multi-year rainfall-runoff data; (b) variability between years for eight selected catchments. From Cheng et al. (2012).

The existence of significant relationships between quantitative indices characterizing the shape of the FDC (e.g., slope of the FDC, parameters of statistical distributions) and climatic and catchment characteristics, such as the aridity index, baseflow index and the precipitation index (Cheng et al., 2012) can enable hydrologically sound regionalisations, including through grouping of similar catchments with the use of more readily available climatic characteristics and catchment characteristics, instead of only using distance, as shown in Figure 7.8 (right panel).

7.2.3 Catchment grouping

The grouping of catchments helps towards the estimation of FDCs in two ways: (a) the classification of catchments underpinning the grouping contributes towards increased understanding of catchment behaviour, and (b) the pooling of similar catchments increases the sample size, and thus improves accuracy and robustness of the estimation of FDCs in ungauged basins. Nevertheless, the scientific literature has not yet reached consensus on the best grouping method or on how to select the most suitable approach, which remains therefore an open problem in the regionalization of FDCs.

The process of grouping catchments involves two steps: (i) the choice of some kind of quantitative similarity index that will serve as the basis for choosing similar catchments, and (ii) a grouping method that uses estimates of the similarity index and organizes the catchments into distinct groups. Section 7.2.2 presented a survey of the indices that can be used to group hydrologically similar catchments. These indices can be based on measured runoff and reflect the signature that is being predicted. Alternatively, the grouping can be done using non-parametric approaches: for example, Ganora et al. (2009) defined a metric to quantify the differences – measured as a distance - between the FDCs and then related these distances to differences among catchments in terms of catchment and climatic characteristics.

If a robust relationship can be found between the slope of the FDC (or any other FDC similarity index) with catchment and/or climate characteristics, then the catchment characteristics or climate classes can be used to delineate the catchments into hydrologically similar groups. One can also use nonparametric approaches to delineating catchment groups on the basis of climate, using several indicators together to group catchments (as was done for seasonal flow regime by Coopersmith et al., 2012, see Chapter 6) or on the basis of surrogates for climate and catchment characteristics, including combinations of these, as the basis for grouping catchments. An example is the baseflow index (e.g., Claps and Fiorentino, 1997; Croker et al., 2003; Cheng et al., 2012), which although derived from runoff reflects the interaction of climate and geology.

One way of grouping catchments is by delineating fixed and contiguous (i.e. geographically identifiable) regions (e.g., Castellarin et al, 2004a; Mohamoud, 2008; Viola et al., 2011). One can expect that contiguous areas will be characterized by similar climate, topography and geology (and all other characteristics which derive from them such as soils and vegetation) give rise to similar catchment hydrological response, and therefore similar FDCs. Of course this is not the only possibility. One catchment can be similar in terms of the processes leading to the FDC to another catchment which is not necessarily contiguous. Cluster analysis seems to be the prevailing approach concerning the regionalization of FDCs with which catchments can be grouped based on the similarity indices discussed above (see e.g., Castellarin et al., 2004a, in central Italy; Sauquet and Catalogne, 2011, in France; Tsakiris et al., 2011, in Massachusetts, USA; Ley et al., 2011, in Germany).

Several methods have been proposed in the literature for grouping catchments. There are algorithms that work directly on basin characteristics through the definition of a measure of distance (e.g. Ganora et al., 2009; Sauquet and Catalogne, 2011). Other clustering algorithms are based on the utilization of non-linear approaches such as regression tree clustering (Sauquet and Catalogne, 2011) or unsupervised neural networks (Self-Organizing Maps, see e.g. Ley et al., 2011). Whether or not the climate or catchment characteristics or a combination of both should be used in the cluster analysis depends on the dominant processes. However, clustering procedures exist to assist in the selection of the most statistically relevant characteristics. For instance some clustering algorithms work on a derived variable obtained by applying e.g. Principal Component Analysis or Canonical Correlation Analysis to catchment characteristics (see e.g. Sanborn and Bledsoe, 2006; Sauquet and Catalogne, 2011).

Whichever clustering method is used it is important to give a hydrological interpretation of the groups. For example, Ley et al. (2011) grouped catchments by training Self-Organizing Maps and implementing hierarchical clustering. They assumed catchments to be similar if the distribution of event runoff coefficients (Merz et al., 2006) and the flow duration curves were similar. The results of their grouping for the Rhineland-Palatinate, Germany are given in Figure 7.12. The spatial arrangement of the clusters is consistent with the distribution of mean annual precipitation. Clusters A and D lie in the high precipitation areas (mean annual precipitation of around 1000 mm), Cluster C in the low precipitation areas (600 mm), and Cluster B lies in between these groups. They note that there is a strong positive correlation between mean annual precipitation and the mean event runoff coefficients. With increasing mean annual precipitation, it is more likely that initial conditions are wet which increases runoff. Climate has the largest influence on runoff, both because of the direct input to runoff at the event scale and through the co-evolutionary processes affecting the drainage characteristics, landform, soils and vegetation (Sivapalan, 2005; Norbiato et al., 2009).

In many cases fixed regions are obtained through clustering. However, from a practical point of view, focused pooling could be an advantage, i.e., clusters identified on the basis of the hydrological affinity with the target site, such as the Region of Influence (RoI) approach (see e.g. Holmes et al., 2002). Studies adopting focused-pooling approaches (see Holmes et al., 2002) predate recent applications of studies based on the identification of fixed and contiguous regions (see for example the studies performed by Mohamoud, 2008 for a Mid-Atlantic Region of USA, by Viola et al., 2011 for Sicily, or by Niadas, 2005 for a Western-Northwestern region in Greece) or application of clustering algorithms (e.g. Sanborn and Bledsoe, 2006, Colorado, USA, clustering on the basis of Principal Component Analysis; Lin and Wang, 2006, Southern Taiwan, clustering algorithm with Self-Organising Maps).

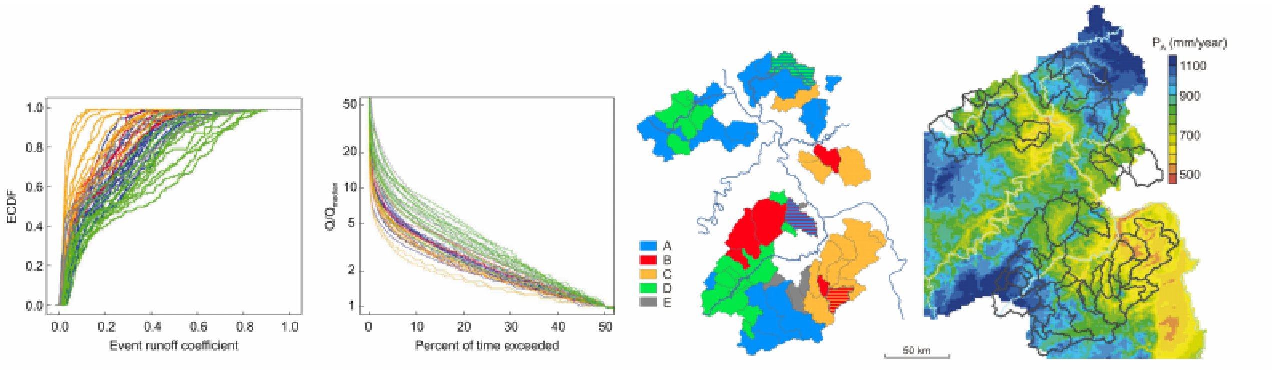

Figure 7.12: Clusters by catchment response behaviour: empirical distribution function of event runoff coefficients ECDF), flow duration curve (Q/Q_{median}), clusters and mean annual precipitation in Rhineland-Palatinate, Germany. From Ley et al., 2011.

The grouping techniques discussed above should always be followed by interpretation and hydrological reasoning. For example, Rianna et al. (2011) applied a cluster analysis using catchment area, altitude and geographical coordinates as explanatory variables, these being the most correlated ones with specific quantiles of runoff. They delineated three regions in this way, which coincide with the Apenninic, coastal and Tiber River zones in central Italy. Since the latter region turned out to be heterogeneous according to a homogeneity test, and because geology was suspected to be the cause, the percentage of substrate (volcanic or carbonatic) was added to the other variables in the cluster analysis and different configurations of the regions were hypothesized. In the end, the Tiber River sub-catchments were divided into two regions at the left and right bank of the river, which are characterised by different substratum. After the further subdivision, all four regions turned out to be statistically homogeneous in terms of shape of the FDCs.

7.3 Statistical methods for predicting flow duration curves in ungauged basins

The grouping methods discussed above can assist in predicting flow duration curves in ungauged basins. The focus of this section is on their prediction with statistical methods on the basis of flow duration curves in neighbouring catchments and catchment/climate characteristics. Methods for estimating flow duration curves in ungauged basins can be classified in many different ways. This chapter reviews the methods by four broad categories; regression methods, index method, geostatistics and methods that use short runoff records.

7.3.1 Regression methods

The regression methods considered in this section are methods that estimate each flow quantile separately from climate/catchment characteristics. The method consists of two main steps. First, a number of empirical runoff quantiles or percentiles (i.e., empirical runoff values associated with a given duration) are regionalized through a series of multi-regression models. Second, the regional estimates of runoff quantiles are analytically or graphically interpolated across the quantiles (see e.g., Franchini and Suppo, 1996; Smakhtin, 2001; Shu and Ouarda, 2010). An early example of regionalization of FDCs reported in the literature is the work of Lane and Lei (1950); their model utilises a variability index, which is a measure of runoff variability specifically related to FDC and calculated as the standard deviation of the logarithms of 5, 15, 25, …, 85 and 95 runoff quantiles. Nathan and McMahon (1991, 1992), used the assumption of linearity of FDC in lognormal space and defined a full curve for ungauged sites by estimating only two runoff quantiles, one from the area of low probability of exceedance (10^{th} percentile) and one from high probability of exceedance (90^{th} percentile, or percent of time with zero runoff for intermittent rivers). Shu and Ouarda (2010) proposed an improved regression based logarithmic interpolation (RBLI) method for FDC estimation at ungauged sites. The RBLI approach integrates regional regression for percentile runoff estimation and logarithmic interpolation to obtain runoff between fixed exceedance percentage points. The proposed procedure uses multiple source sites for information transfer and introduces three different weighting schemes (geographical distance weighted, drainage area weighted and catchment characteristics weighted) to be used with the multiple source sites FDC based approach in an effort to maximize the use of regional information.

Quantile regression generally makes no assumptions concerning the distribution or shape of the FDC (but there are exceptions, see e.g. Franchini and Suppo, 1996) and avoids the normalization by an index runoff and the use of a regional dimensionless FDC. Quantile regression focuses on the regionalization of runoff percentiles, which have a clear physical meaning and are generally straightforward to model through regional regression relationships, particularly for low and medium durations. On the one hand, when a sufficient number of quantiles are regionalized, the method may produce smooth and continuous FDC predictions and provides runoff estimation for the full range of exceedance probability values. However, regressing a large number of runoff quantiles means a large number of multi-regression models to be identified; also, the practical application of regression model to ungauged basins may result in inconsistent estimates of the runoff quantiles, that is the estimate of $Q(D_1)$ may be smaller than the estimate of $Q(D_2)$, with durations $D_1 < D_2$. Archfield (2009) and Archfield et al. (2010) employ a recursive regression approach to ensure that such inconsistent results do not occur.

7.3.2 Index flow methods

The index flow methods considered in this section include two types of method. (a) The first are parametric methods where the parameters of a distribution function representing the flow duration curve are regionalised. (b) The second method assumes that the flow duration curves scaled with an index flow of all catchments in a region are assumed to be the same. The two methods are grouped under index flow methods here because in both instances some rescaling of the flow duration curve is involved. For both methods an index-flow is needed that needs to be estimated for the ungauged basins. The index-flow is, typically, the mean annual runoff (see e.g. Smakhtin et al., 1997; Ganora et al., 2009) or the median daily runoff (see e.g. Ley et al., 2011).

Parametric methods:

A general parametric approach may use models for representing the normalized FDCs, parameterising the model and regionalising its parameters through regression (see e.g., LeBoutillier and Waylen, 1993a and 1993b, Castellarin et al., 2004a and 2007). The approach is generally implemented as follows: a suitable frequency distribution is chosen as the parent distribution for a particular region; the distribution parameters are estimated on a local basis for the gauged river basins located in the pooling group of sites using the runoff observations; regional regression models are then identified for predicting the distribution parameters on the basis of the geomorphological and climatic characteristics of the basins. The frequency regime of daily runoff may not be accurately described by theoretical distributions with less than four parameters (see e.g., LeBoutillier and Waylen, 1993a; Castellarin et al. 2004a and 2007; Archfield, 2009). This statement, true in principle, conflicts with the practical need to limit the number of parameters. A small number of parameters increase the chance of assigning clear meaning to each one (e.g., position, scale, shape) and a small number of multi-regression models need to be identified during the regionalisation phase.

Castellarin et al. (2004a) proposed a model of FDCs that analytically relates annual FDCs to long-term FDCs (Vogel and Fennessey, 1994). The model is able to capture the inter-annual variability of AFDCs without representing the serial correlation and seasonality of daily runoff. This is accomplished by standardizing the daily runoff by dividing by the annual runoff for the year in which the runoff occurred. This simple step avoids the need for more complex theoretical analyses requiring assumptions regarding the stochastic structure of daily runoff series, such as persistence and seasonality (Castellarin et al., 2004b). The model assumes that daily runoff is the product of two independent random variables, an index-flow (assumed equal to the annual runoff) and dimensionless daily runoff. The index flow represents the variability between dry and wet years and it is mainly controlled by annual precipitation. The dimensionless daily runoff represents the within year variability which is mainly controlled by climate, size and permeability of the basin.

Castellarin et al. (2007) represents the distribution of the index flow by a 2-parameter logistic distribution, and the distribution of the dimensionless daily runoff by a 3-parameter kappa distribution (i.e., a 4-parameter kappa distribution with unit mean). They estimated the position parameter of the logistic distribution (which represents mean annual runoff) by regressions from area and mean annual net precipitation and, the scale parameter which represents the between-year variability of annual runoff) from the variability of annual net precipitation. The position parameter of the kappa distribution (which represents the within-year variability) was estimated from catchment permeability and elevation range. They showed by cross-validation that the model outperforms traditional parameter regression models that focus solely on the long-term FDC, without describing inter-annual variability explicitly. In interpreting the catchment characteristics they found that when predicting FDCs in ungauged basins it is important to consider the full range of runoff processes controlling the FDC. On the one hand these are processes that operate at the event and seasonal time scales and are represented by the precipitation inputs, elevation gradients and subsurface permeability. On the other hand, processes at longer time scales may be involved through the co-evolution of catchments. For example, higher precipitation rates in a catchment may lead to different land forms and soil types than in a low precipitation catchment. Long term precipitation is then no longer an index of precipitation input alone but also an index of the landform and soil processes that control the FDC.

In the central Italian context of the work of Rianna et al. (2011), basin area and mean annual precipitation appear to control the high flow limb of the FDC while the geological heterogeneity controls the low flows. They apply an adaptation of the model to intermittent streams and illustrate a regional application of the model in cross-validation. Shao et al. (2009) also report a parametric model for interpreting and predicting the no flow fraction as a function of basin characteristics. Li et al. (2010) regionalised the parameters of lognormal distributions representing the FDC across Australia. Figure 7.13, taken from Li et al. (2010), show that the performance of their index method (within catchment Nash-Sutcliffe efficiency (NSE) calculated on several quantiles of the FDC) outperforms other standard methods such as linear regression, nearest catchment and a method based on hydrologic similarity. One advantage of the model proposed by Li et al. (2010), which is central to the scope of this book, is the fact that results can be interpreted hydrologically since the relative importance of the model parameter of interest is quantified by the magnitude of the coefficients. For instance they found that the position of the FDC (which is related to the mean annual runoff) is positively correlated with the mean annual precipitation and negatively correlated with mean annual potential evaporation. This is in line with the general understanding of the Budyko curve, which indicates that the aridity index is the dominant control on mean annual runoff (see chapter 5). The FDC parameter related to the standard deviation of runoff is strongly related to both the standard deviation and mean annual precipitation. The standard deviation of runoff increases with decreased mean annual precipitation, indicating higher runoff variability in drier catchments. The standard deviation of runoff is also affected by the presence of vegetation in the catchment, as represented by leaf area index (LAI). It can be seen that the variability of runoff decreases with the leaf area index, suggesting lower runoff variability from more heavily vegetated catchments. The model of FDC used by Li et al. (2010) also includes a non-cease-to-flow parameter (i.e., observed non-zero flow proportion), which is mainly affected by the aridity index, as would be expected, but also by elevation difference, since for catchments with steeper slopes it is more likely to experience cease-flow conditions. Woody vegetation increases the possibility of having cease-flow days as it is capable of extracting soil moisture leading to decreased base flow. Interestingly, as opposed to other studies, catchment area and geographic location does not appear sufficiently explanatory for the shape of the FDC: firstly, because specific runoff data are used, and secondly, most of the influence of geographical locations has been explained by other covariates.

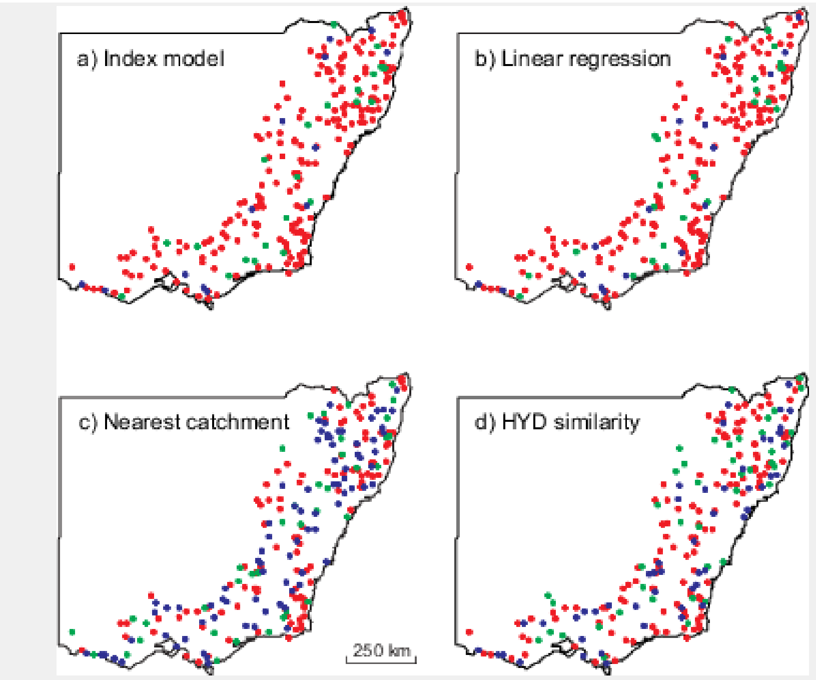

Figure 7.13 - Nash-Sutcliffe efficiency (NSE) of quantiles of the FDC obtained from four regional models in southeast Australia. Three colours denote three categories based on the range of within-catchment NSE (red: above 0.75; green: between 0.5 and 0.75; blue: below 0.5). From Li et al. (2010).

Rescaled flow duration curve:

These methods are based on rescaling the flow duration curve by an index flow and assume that the scaled flow duration curve does not vary within a homogeneous region. Two steps are needed, i) identification of pooling groups of gauged sites which can be assumed homogeneous in terms of the scaled FDC, and ii) the definition of an allocation rule to assign ungauged sites to a group. In the European FRIEND (1989) study, dimensionless daily FDCs were averaged within pooling groups of catchments. A similar approach was used by Hughes and Smakhtin (1996) and Smakhtin et al. (1997) to construct seasonal FDCs for one of the primary drainage regions of South Africa, and by Castellarin et al. (2004a) to construct six dimensionless daily FDCs for six hydrologically similar pooling groups of sites (see also Chapter 11 "Case Studies"). Ganora et al. (2009) presented the construction of regional dimensionless FDC, in which the pooling group of gauged sites is identified through cluster analysis using a distance metric that quantifies the dissimilarity between pairs of curves, and the FDC of each cluster is identified as the mean normalized duration curve. Minimum catchment elevation and, less importantly, mean hillslope length are found to be the best explanatory variables for catchment grouping in the north-western Italian and Swiss context of the study by Ganora et al. (2009) and were used to subdivide the study area into two homogeneous regions (Figure 7.14). The minimum catchment elevation could be interpreted as a surrogate for the seasonality of flow regimes in the region, which is controlled by snow, glaciers, and precipitation regime in Alpine catchments as opposed to low-land mixed regimes and the Appennine-Mediterranean bimodal regime in the south-east of the region (with lower elevations). Similarly, in Nepal, Arora et al. (2005) use elevation in their relationship for non dimensional flow since more variability happens at higher elevations. Regime is controlled by snow, glaciers and precipitation (of which elevation and area are surrogates), and the regime curve controls the FDC, as discussed in section 7.2.

Croker et al. (2003) proposed a theoretical framework to address the construction of FDCs in arid regions of the world with ungauged ephemeral or intermittent streams. They presented a regional model to estimate the probability of zero/non-zero flows for Portuguese ungauged river basins. The model estimates the probability of zero-flows as a function of the mean annual precipitation, as a surrogate of both geographical location and climatic conditions, allowing the derivation of FDCs for ungauged river basins, either ephemeral or perennial.

Parametric methods and rescaled flow duration curve methods are complementary. Parametric methods enable one to model the entire curve, resulting in runoff estimates associated with any duration of the flow duration curve but, often more than three parameters are needed to fit the observed distribution well and it may be difficult to regionalise three or more parameters (Castellarin et al., 2007). The main advantage of rescaled flow duration curve methods is that there is no need to fit a distribution function, but identifying a homogenous group may be more important. Also, the index flow (usually the annual runoff) needs to be estimated in the ungauged basin. Methods for predicting annual are discussed in Chapter 5.

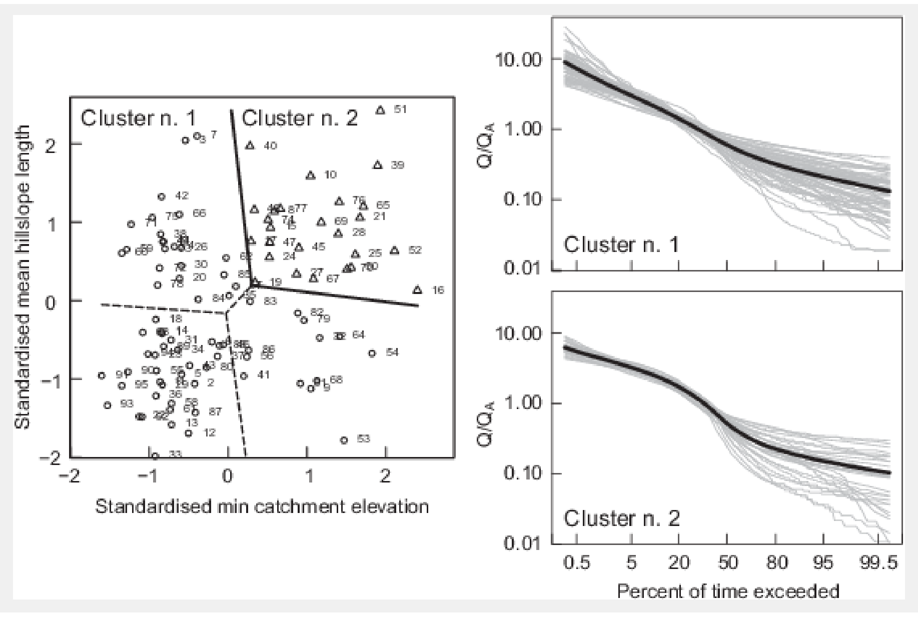

Figure 7.14 (left) Non-contiguous regions in the space of catchment characteristics (standardised to have zero mean and unit variance). The dashed lines represent the boundaries between the four clusters obtained before merging the clusters whose FDCs cannot be considered significantly different. The final two disjoint regions are separated by the solid line. (right) Flow duration curves grouped by cluster (grey) and corresponding regional curves (black). From Ganora et al. (2009)

7.3.3 Geostatistical methods

Recent studies have proposed several regionalization approaches that depend only partially, if not dispense with, the delineation of a homogeneous pooling-group of sites, which is a critical phase and a common prerequisite for the application of FDC regionalisation approaches (Grimaldi et al., 2011). These approaches apply geostatistics criteria to the challenge of regionalising hydrological information. The first is called Physiographic Space-Based Interpolation (PSBI), or Canonical kriging, and performs the spatial interpolation of the desired characteristics of the FDC in terms of geomorphoclimatic characteristics (Chokmani and Ouarda, 2004; Castiglioni et al., 2009). The second technique, named Topological kriging or Topkriging, is analogous to a spatial interpolation method for runoff-related variables, which interpolates the runoff value of interest (i.e., low-flow indices, annual runoff, etc.) along the stream network by taking the area and the nested nature of catchments into account (Skøien et al., 2006; Skøien and Bloschl, 2007; Castiglioni et al., 2009).

These approaches are particularly appealing for predictions in ungauged basins as they provide a continuous representation of the quantity of interest along the stream network (Topkriging), or in the physiographic space (PSBI). Potential applications of these approaches include the estimation of FDC in a region (see e.g., Skøien and Blöschl, 2007; Castiglioni et al., 2009). Some preliminary studies show application of PSBI to the problem of FDCs, the analyses apply a three-dimensional kriging technique for interpolating long-term dimensionless FDCs in the physiographical space. The horizontal coordinates are the first and second canonical variables of the set of available catchment characteristics (i.e. two-dimensional physiographic space), whereas the vertical coordinate is the runoff duration (see Figure 7.15).

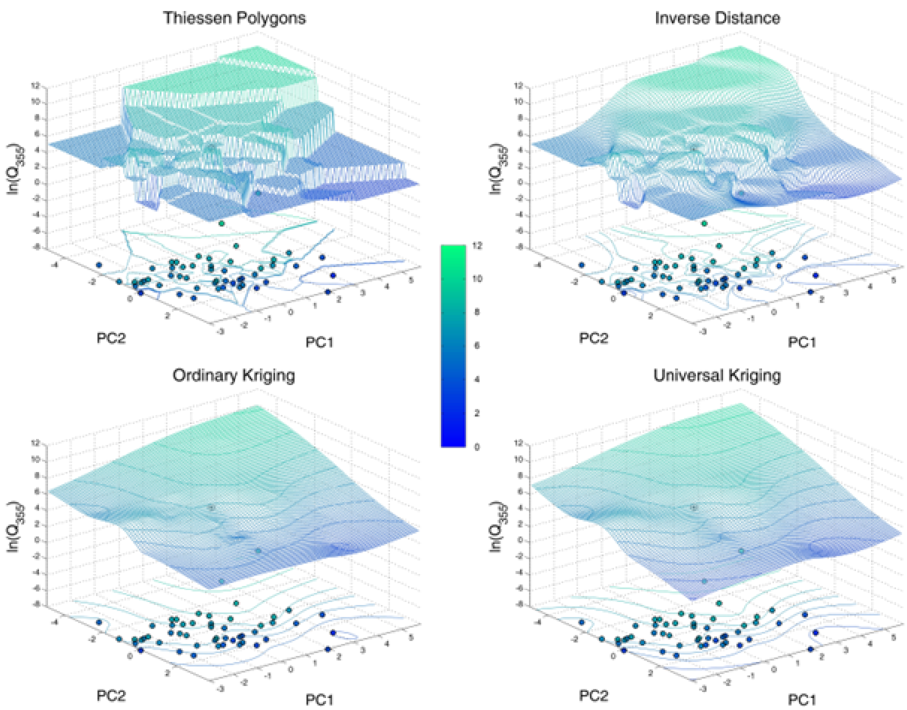

Figure 7.15 - Spatial interpolation in the principal component space for the estimation of a quantile of the FDC (Q_{97} low flow). Representation of the surfaces generated in the space of catchment characteristics by four different techniques for the River Aterno at L'Aquila, Italy. From Castiglioni et al., (2009)

7.3.4 Estimation from short records

Castellarin et al. (2004a) presented a series of resampling experiments to assess the sensitivity of empirical FDCs to the sample length (see Chapter 11 "Case Studies" for more details). The analysis considers a number of river basins with long series of daily runoff, and compares the cross-validated FDCs predicted with three different regional approaches (i.e. quantile regression, parametric and non-parametric) with empirical estimates of long-term FDCs based upon a few years of observation (one, two and five years). This resampling experiment shows that predictions of long-term FDCs based upon five years of observed runoff largely outperform the best performing regional model, while one or two years of daily runoff are generally sufficient to obtain predictions of FDCs that are as accurate as the ones retrieved through regionalization. This result highlights the value associated with observed runoff, even for short series. As a general remark, the regional estimation of the FDC for ungauged basins should be performed, where possible, by applying different approaches and selecting the estimated FDC only after a scrupulous analysis of the suitability of each regional model to the particular sub-region where the ungauged site is located (Castellarin et al., 2004a). Also, it is generally not advisable to rely completely on any regional model, which should be used to provide a first order approximation of FDCs. The practical utilisation of the estimated FDC for design purposes should be supported through additional, perhaps *ad-hoc* measurement campaigns.

7.4 Process based methods of predicting flow duration curves in ungauged basins

Deciphering the separate controls of both climate processes (e.g., precipitation, temperature, radiation or potential evaporation) and catchment characteristics (i.e., soil, topography, vegetation type and functioning, catchment size, human impacts) on the shape of FDCs represents a key issue for hydrologists. This issue can be best addressed by using process based approaches which link the drivers (input fluxes of water and energy), the state of the system (storage terms) and its response (output fluxes). To be most effective, process based methods need to include, as a basic ingredient, the time variability of precipitation inputs to a catchment at all time scales, extracted from available observations. They need to describe how this variability is propagated through the catchment system, and finally manifest in the catchment's FDC. In this way, process based methods provide an excellent basis to interpret (or reinterpret) and evaluate the results from application of well-established statistical methods, as well as evaluate possible changes in the FDC induced by observed or predicted changes to the climatic drivers (e.g., precipitation) or landscape characteristics (e.g., land uses).

Work on predictions of FDCs, especially in ungauged basins, has been mostly statistical and empirical, which has gained strength in the last two decades. However, application of process based approaches has lagged behind, no doubt due to the difficulties of merging the statistical and dynamical aspects of runoff variability, especially over a wide range of time scales, as is required in the case of the FDCs. Indeed, in this respect, the comparison with derived distribution methods in flood frequency (see Chapter 9) is quite stark. If the FDCs are brought up at all in the context of process based modelling, they appear to be just one outcome or by-product of continuous rainfall-runoff models. For example, FDCs are used as one of the signatures of runoff variability (Farmer et al., 2003), or are used in the calibration or performance assessment of rainfall-runoff models (Westerberg et al., 2011). Only in rare instances is the estimation or prediction of the FDCs the actual goal of the modelling (Mostert et al., 1993; Tshimanga et al., 2011), and even then these applications are in gauged catchments, and applications in ungauged catchments is conspicuously absent.

In recent times there have been several efforts that have begun to approach FDCs from a process perspective. The focus so far has been developing understanding of the climatic and catchment controls on the FDCs, very similar to the steps that were made in the early days of the derived flood frequency work (e.g., Eagleson, 1972; Sivapalan et al., 1990). These methods have not matured enough to the point that they can be used to predict FDCs in ungauged basins, but they show considerable promise. Therefore, in the sections below a brief summary is given of these approaches, and highlight their main strengths and weakness (so far), with a view to recognising the importance of such work for predictions of FDCs in ungauged basins, to complement the significant advances made through statistical methods. As in all other chapters, this review is organised into two parts: (1) derived distribution approaches that aim to capture the process controls on the FDCs in an analytical or quasi-analytical way so as to provide process insights into the regional patterns that arise from statistical methods, and thus can improve regionalisation efforts, and (2) continuous rainfall-runoff simulation methods that generate continuous runoff time series, from which FDCs can be constructed, but nevertheless enable sensitivity studies that will again provide insights to observed patterns.

7.4.1 Derived distribution methods

Flow duration curves may be derived from precipitation analytically similar to the derived flood frequency method of Eagleson (1972) with a number of simplifications. Botter et al. (2007a) adopted a stochastic-analytical model that consists of, i) a simple lumped (deterministic) model subsurface drainage (slow flow), governed by a field capacity threshold, and a characteristic residence time; and ii) stationary sequences of random precipitation events, whose arrival times are Poisson distributed, and precipitation depths are gamma distributed. The rainfall-runoff model enabled them to estimate slow flow volumes analytically which, when combined with the statistical characterisation of the precipitation, enabled them to derive the probability density function of slow flow volumes, which represents a form of the slow flow component of the FDC. The analytical formulation also enabled them to relate the runoff variability to the underlying catchment properties and key precipitation event characteristics.

Subsequently, the earlier model of Botter et al. (2007a, b) has been extended by Muneepeerakul et al. (2010) to include a *fast flow component* as well and by Botter et al. (2009) to include non-linearities in the subsurface storage-runoff relationship. The ability of the stochastic dynamic model to reproduce observed FDCs has been tested in several catchments in the USA and Europe (Botter, 2010). Although the stochastic-dynamic framework (e.g., Botter et al., 2007a,b; 2009; 2010) is capable of providing insights into the climatic and catchment controls of the FDCs, its potential for application to ungauged basins is constrained by the assumptions made in the work done to date (e.g., Poisson precipitation arrivals). In circumstances where there is strong seasonality in the climate inputs, constant (but different) parameter values have been adopted for each season. The routing of runoff in the river, and the associated time delays, and in particular, the carryover of soil moisture storage between seasons has been neglected, so that the method works best in places where seasonality is low. This highlights the need for a more general framework, one for the entire year that captures within-year variations in climate and soil moisture storage, especially in the light of the strong role that seasonality plays in controlling the middle part of the FDC, the role played by hydrogeology and long flow pathways that control low flows, and the role played by high precipitation events that govern high flows.

Yokoo and Sivapalan (2011) proposed a conceptual framework to reconstruct FDCs by disaggregating the flow duration curves of total runoff into two components, i.e., *fast flow* duration curves and *slow flow* duration curves, similar to the earlier work of Botter et al. (2007) and Muneepeerakul et al. (2010). The approach of Yokoo and Sivapalan (2011) was formulated on the basis of numerical simulations of the water balance of hypothetical catchments with the use of a physically based rainfall-runoff model, and driven by artificial precipitation inputs generated by a stochastic rainfall model. These simulations by Yokoo and Sivapalan (2011) revealed a clear relationship between the fast flow FDC and the duration curve of precipitation (PDC) and between the slow flow FDC and the catchment's runoff regime curve (mean seasonal runoff). In doing so Yokoo and Sivapalan (2011) have proposed a new conceptual framework for the estimation of FDCs in ungauged basins, through building bridges between the fast and slow flow parts of total runoff as precipitation variability cascades through the catchment system, and through recourse to understanding the respective process controls. Yokoo and Sivapalan (2011) carried out preliminary analyses on a few selected catchments within the United States to demonstrate the feasibility of their approach. However, their approach has also not been applied and tested in ungauged catchments. Nevertheless, there is promise that through a combination of the stochastic dynamic approach of Botter et al. (2007) and Muneepeerakul et al. (2010), and the numerical simulation approach of Yokoo and Sivapalan (2011), that one can make considerable advances in the area of process based approaches to the predictions of FDCs in ungauged basins.

7.4.2 Continuous models

Long-term numerical simulations of the soil water-balance equation coupled to some routing scheme to reproduce the movement of water in soils and streams are greatly beneficial to explore the dependence of the features of the FDC on the underlying hydrological and climatic processes, as all the driving processes (precipitation, soil moisture dynamics, transport in channels and hillslopes) may be described in much more detail than that which may be possible with analytical models. An example of continuous model simulations to describe FDC is described in the following, and refers to the approach developed by several authors, using the Pitman (1973) monthly rainfall-runoff model, which has been used extensively in southern Africa, particularly in ungauged catchments. The most recent description of the model is provided in Hughes (2006). This conceptual model includes the primary processes that are responsible for the magnitude and shape of the FDC: surface runoff (based on a triangular distribution of catchment absorption rates and monthly precipitation total), a non-linear drainage function dependent on the moisture soil moisture storage level partitioned into rapid (interflow) and slow (groundwater) components, the latter accounting for groundwater recharge and runoff components. The balance between the contributions of the three components (surface runoff, interflow and groundwater discharge) determines the shape of the FDC and this balance is clearly a reflection of the climate and catchment characteristics (as represented by the model parameters). The model also can simulate the effects of anthropogenic impacts (abstractions, reservoir storage, impacts of different vegetation cover, etc.) on FDCs (Hughes and Mantel, 2010).

One way of assessing the model performance is to compare simulated FDCs to either FDCs derived from gauged data or regionalized estimates of the FDCs for ungauged situations. Figure 7.16 shows results for two dry catchments in Botswana and Zimbabwe. For the ephemeral river in Botswana, while most of the FDC is able to be simulated, the frequency of zero flow is much more difficult to capture even after calibration. This may be related to poor precipitation definition in semi-arid areas, but may also be related to some processes not being adequately represented by the model (e.g. dynamic vegetation changes, see Mostert et al., 1993). For the perennial (but relatively dry) river in Zimbabwe (Figure 7.16b), the results indicate poor agreement in the case of low flows and part of the reason for this can be attributed to upstream development impacts (small farm dams, etc.) on the observed runoff data.

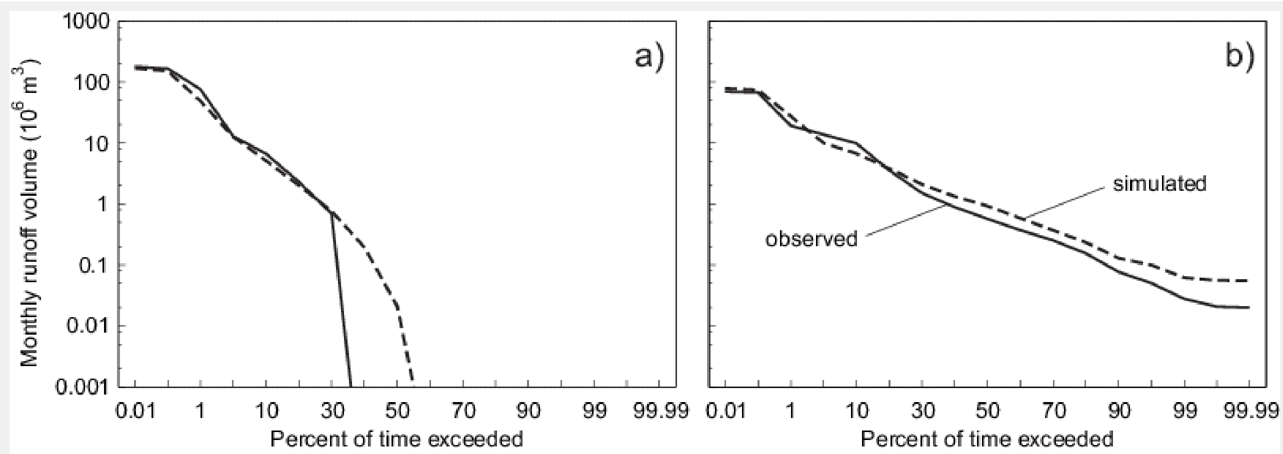

Figure 7.16 - Simulated monthly flow duration curves in (a) a dry region (Tati catchment, Botswana, 570 km^2) and (b) a somewhat wetter region (Mwarazi, catchment, Zimbabwe, 202 km^2).

While all of the results given above, and also those extracted from a related report (Hughes, 1997a, 1997b), include model calibrations, and are therefore not applications in ungauged basins, one of the conclusions was that variations in parameter values were generally a reflection of what might be expected given the conceptual interpretation of the model structure and the limited knowledge available about the physical catchment characteristics of the sites used. These observations plus additional experience over many years of applying the Pitman model contributed to the development and application of parameter estimation approaches for the Pitman model, as reported in Kapangaziwiri and Hughes (2008). The approach adopted for parameter selection in Kapangaziwiri and Hughes (2008) is based on *a priori* estimation of most of the parameters of the Pitman model using estimates of physical basin properties. The results for selected basins show that the revised parameters are at least as good as regionalised sets (using techniques discussed in Chapter 10) or give satisfactory results in areas where no regionalised parameters exist. However, in order to make the approach applicable to ungauged catchments, the remaining parameters, mostly associated with interception and evaporation processes, should be also estimated *a priori* (without calibration).

Hughes and Mantel (2010) used the Pitman model for Monte Carlo sampling from parameter probability distributions to generate ensemble outputs of time series and therefore also estimates of uncertainty of FDCs. This may be useful for ungauged basins where it is difficult to evaluate the applicability of a single regionalised parameter set. An example of this application is presented in the Case Study chapter (Chapter 11). Some of these principles have been applied to setting up the model for the large Congo River basin (Tshimanga et al., 2011). Figure 7.17 shows two examples of initial uncertainty estimates based on FDCs for the upper parts of the Congo River basin. The uncertainty is quite large and in some cases (e.g., low flows for sub-basin 82) biased relative to observed low flows. There also appears to be a problem with over-prediction of runoff peaks, which may be related to inadequate storage, infrequent excessive surface runoff generation, or inadequate attention to attenuation of flood peaks due to floodplain storage. The use of FDCs has allowed these model deficiencies to be identified, and has prompted further study towards model improvement.

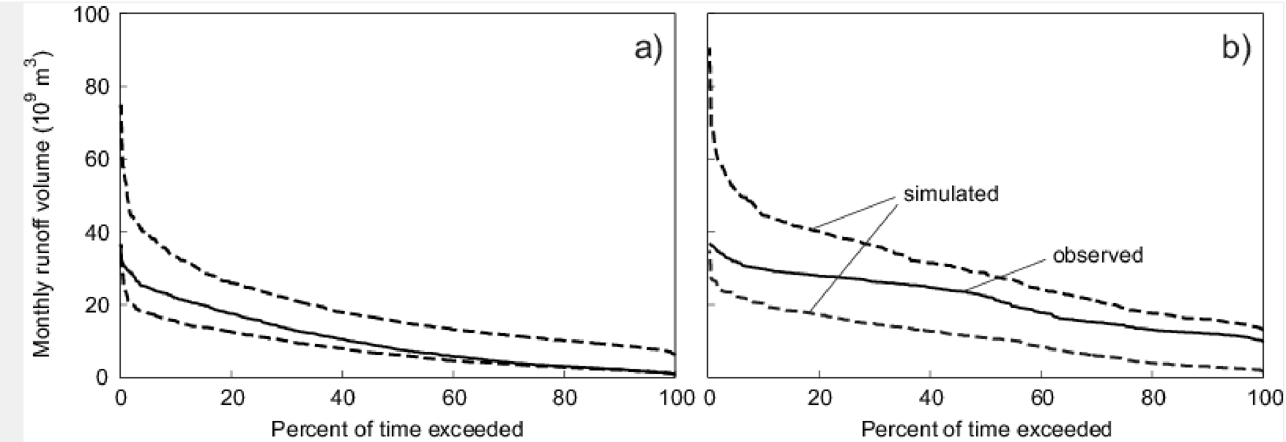

Figure 7.17 - Uncertainty simulation results for two of the gauged upper catchments in the Congo River basin. a) Sub-basin 82, b) Sub-basin 85. Dashed lines show XX uncertainty bounds. From Tshimanga et al., (2011).

Even though the use of continuous models allows for a more detailed description of the driving processes, it has the consequence of significantly increasing model complexity, possibly increased accuracy, but also lengthening simulation times and increasing the number of parameters. As a result, there is a danger that the individual role of each climatic factor and hydrologic process in contributing to the shape of the FDC cannot be isolated easily, leading to limited transferability to catchments in other catchments/climates. A range of approaches are therefore needed for introducing process understanding into predictive models, ranging from simple, targeted models to complex, distributed models. In future, process based methods should be designed in such a way to benefit from and complement the experiences arising from well-established statistical methods, and in this way to help improve the performance of statistical regionalisations as well (see e.g., Di Prinzio et al., 2011).

7.5 Comparative assessment

The aim of the comparative assessment of flow duration curve predictions in ungauged basins is to learn from the similarities and differences between catchments in different places, and to interpret the differences in performance in terms of the underlying climate-landscape controls. Understanding these controls sheds light on the nature of catchments as complex systems and provides guidance on what methods to choose in a particular environment. The assessment is performed at two levels (see Chapter 2.4.3). The Level 1 assessment is a meta-analysis of studies reported in the literature. The Level 2 assessment involves a more focused and detailed analysis of individual basins from selected studies of Level 1, in terms of how the performance depends on climate and catchment characteristics as well as on the method chosen. In both Level 1 and Level 2 assessments, the performance was evaluated by leave-one-out cross-validation, where each catchment was treated as ungauged and the runoff predictions were then compared to the observed runoff. The performances obtained by the comparative assessment are estimates of the total uncertainty of runoff predictions in these ungauged basins.

7.5.1 Level 1 assessment

Table A7.1 lists 13 studies that deal with the estimation of FDCs in ungauged basins. Some of the studies reported performance measures that were not compatible with the other studies and/or performed goodness of fit analysis instead of cross validation. The remaining 10 studies performed leave-one-out cross validation and the performance measures were broadly similar. These were used in the Level 1 assessment (indicated in Table A7.1). The number of catchments evaluated in each study ranges from 8 to 1080, with a median of 49. There are several studies that compare different hydrologic models and/or regionalisation approaches which results in total of 27 results for predictive performance. The regionalisation methods used are index methods, regression approaches and estimation from short records. The studies are quite heterogeneous in terms of performance measures and the way they were applied. Typically applied performance measures are: the absolute normalised error in the centre of the FDC; the proportion of sites with Nash-Sutcliffe (NSE) calculated over quantiles lower than 0.75; the proportion of sites with absolute normalised error (ANE) lower than 1; and the mean relative root mean squared error. Even though these performance measures are not strictly speaking comparable, values close to 0 imply good performances, and large values imply a lower performance. Note that these all represent errors (rather than skill), so they have been plotted downwards on the vertical axis to make them consistent with the performance measures in the other chapters, i.e. higher up in the plot is better. Different performance measures were indicated by different symbols in the plots. For comparison with the other runoff signatures in Chapter 12, the NSE of the quantiles of the FDC were back-calculated from the percentage of sites with the NSE lower than 0.75 by applying an empirical relationship from Level 2. The 25% and 75% quantiles of these NSE are 0.60 and 0.90, respectively.

Fig. 7.18 and Table A7.1 indicate that the studies were performed in Europe, Asia, Australia and North America. Most available studies were for humid and tropical climates. Three main science questions are addressed below.

Figure 7.18 Map indicating the countries included in the Level 1 assessment.

How good are the predictions in different climates?

In Figure 7.19 it is important to compare similar performance measures. The absolute normalised errors (full circles) in humid regions are smaller than those in the arid regions. The proportion of sites with NSE lower than 0.75 (plusses) in humid regions show some scatter and the majority of them are larger than that for the cold regions. This means that from this limited comparison there is a tendency for the regionalization methods in humid regions to perform slightly better than in tropical regions and slightly lower than in cold regions.

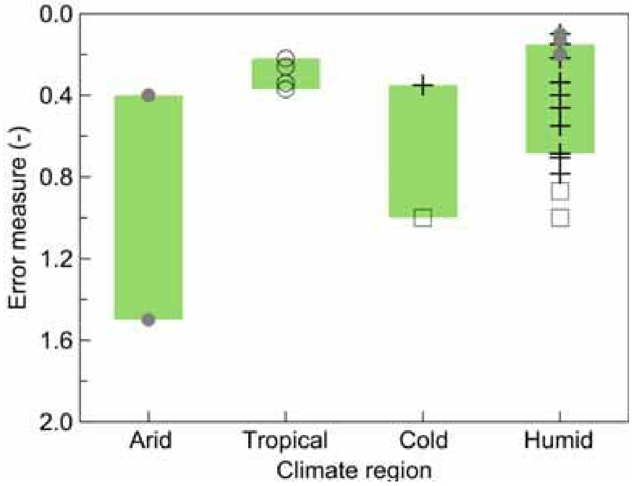

Figure 7.19 Absolute normalised error in the centre of the FDC (full circles), the proportion of sites with Nash Sutcliffe efficiency (NSE) calculated over quantiles lower than 0.75 (plusses), the proportion of sites with absolute normalised error (ANE) lower than 1 (empty squares), and the mean relative root mean square error (empty circles) of predicting FDCs in ungauged basins stratified by climate. Each symbol refers to a result from the studies indicated in Table A7.1. Boxes show 25%-75% quantiles.

Which method performs best?

The regionalisation methods represented in the assessment included 13 results for index methods, 11 results for regression approaches and 3 results for estimated FDC from short records of 1, 2, 5 years. The assessments in each group are not based on exactly the same regionalisation approach, but the methodology is similar. Figure 7.20 indicates that methods using short records seem to have the best performance, even though there are few studies. The study that compared all three methods for the same catchments using the same performance measure (shown in Fig. 7.20 as grey line) shows that predictions of long-term FDCs based upon 1, 2, 5 years of observed runoff all outperform any of the other methods. More detailed comparisons Castellarin et al. (2004a) with other error measures suggest that 5 years of observed runoff give better estimates of FDC in all respects but for 1 and 2 years it depends on the error measure examined. The study that compared the index method with two quantile regression method found that that the two regression methods resulted in the same performance which was better than that of the quantile regression. However, this comparison was only over two catchments. In both comparative studies, the regressions methods perform better than the index method, but when one considers all studies the index method performs better.

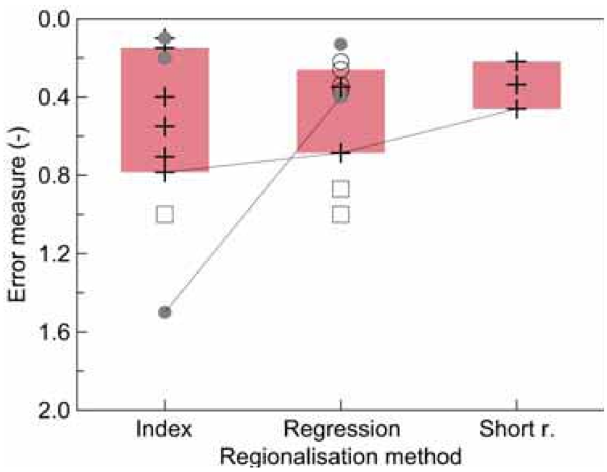

Figure 7.20 Absolute normalised error in the centre of the FDC (full circles), the proportion of sites with Nash Sutcliffe efficiency (NSE) calculated over quantiles lower than 0.75 (pluses), the proportion of sites with absolute normalised error (ANE) lower than 1 (empty squares), and the mean relative root mean square error (empty circles) of predicting FDCs in ungauged basins stratified by regionalisation method. Each symbol refers to a result from the indicated in Table A7.1. Lines indicate studies that compared different methods for the same set of catchments. Boxes show 25%-75% quantiles.

How does data availability impact performance?

Figure 7.21 shows that performance increases with the number of catchments used in the analysis. The trend is particularly clear for the comparison of the pluses for the intermediate classes of catchment number (from 20 to 250 catchments per study). Also, the comparison between the smallest and largest class (full circles) is clear. Statistical regularity would suggest that the smaller sample sizes would account for some of this decrease in performance. This is consistent with other studies that have evaluated the effect of sample size on regionalisation (Spence et al., 2007). This trend is due to the higher stream gauge density in the larger studies. These results suggest that even if one is interested in estimating a FDC for a single catchment it may be worth basing the regionalisation on a large number of catchments.

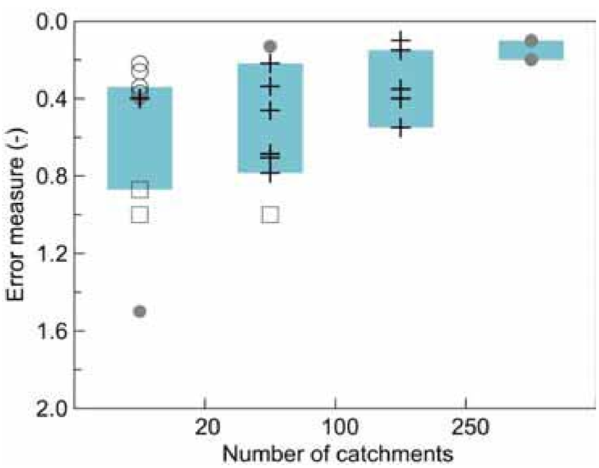

Figure 7.21 Absolute normalised error in the middle of the FDC (full circles), the proportion of sites with Nash Sutcliffe efficiency (NSE) calculated over quantiles lower than 0.75 (plusses), the proportion of sites with absolute normalised error (ANE) lower than 1 (empty squares), and the mean relative root mean square error (empty circles) of predicting FDCs in ungauged basins stratified by the number of catchments within each study. Each symbol refers to a result from the studies indicated in Table A7.1. Boxes show 25%-75% quantiles.

Main findings of Level 1 assessment:

- In humid regions the performance of predicting flow duration curves in ungauged basins tends to be better than in arid climates.
- Methods that use short runoff records at the site of interest perform better than any regionalisation method provided at least one year of daily runoff data is available, and significantly better if two to five years of data are available.
- The performance increases clearly with number of stream gauges in the region.

7.5.2 Level 2 assessment

The Level 1 synthesis of existing studies (Table A7.1) clearly showed that many studies only report summary statistics of regionalization performance and/or catchment characteristics, which hampers detailed attribution of the performance and inter-study comparison of results. The objective of the Level 2 synthesis is to examine and explain the performance of the regionalization methods in greater detail. Four study authors from the Level 1 assessment, plus three other authors provided detailed information about climate and catchment characteristics in a consistent way and reported the regionalization performance for each catchment (Table A7.2). This dataset combines data from 1419 catchments, four groups of regionalization methods and four catchment characteristics. The regionalization methods are: regression approaches, index methods, geostatistics and process based methods. The catchment characteristics are aridity (potential evaporation by mean annual precipitation), mean annual air temperature, mean elevation and catchment area.

The performance assessment was based on the slope of the middle part of the FDC defined as the difference between the 30% and 70% normalized runoff quantiles divided by 40. This slope quantifies the relative change of runoff for 1% difference in exceedance probability. It was chosen for this analysis because it is a specific feature of the FDC, while the upper and lower parts of the FDC are related to floods and low flows treated in the chapters 8 and 9. Furthermore it is related to the variance of daily runoff and to climate and catchment processes as discussed in section 7.2. The performance was then calculated as the normalized error (NE) and absolute normalized (ANE) (Table 2.2) of the slope. The NE highlights biases in the methods while the ANE is a measure of the overall performance. Note that the ANE is an error measure, so it has been plotted downwards on the vertical axis to make it comparable with the performance measures, i.e. higher up in the plot is better. For comparison with the other runoff signatures in Chapter 12, R^2 of the slope of the FDC were calculated for all methods in each study separately which gave a median of 0.26. Also the NSE of the quantiles of the scales FDC were calculated which gave a median of 0.98. Other evaluation measures may lie in between. As an indicative range of typical performances a range of 0.40 to 0.95 is shown in Chapter 12.

To what extent does runoff prediction performance depend on climate and catchment characteristics?

The assessment of the predictive performance of the different methods with respect to the four climate and catchment characteristics is presented in Fig. 7.22 and Fig. 7.23. The top panels of both figures show the dependence of performance on aridity. For the regression method performance clearly decreases with aridity. For the most arid catchments (aridity indexes between 1 and 2), the regression approach tends to overestimate the slope of the FDC (Figure 7.23). For all the other methods the decrease in performance with aridity is less clear, perhaps with the exception of the process based methods. It should be noted that the methods were applied to different regions: regression to France and the USA, and the other methods to Austria and northern Italy where the catchments are never very arid. While, generally one would expect a decrease of performance with increasing aridity since arid regions tend to be more heterogeneous than humid ones there may also be differences in the results of the different methods that are related to differences in the regions. A similar, but less pronounced pattern can be observed for the relationship between performance and mean annual temperature T_A (second panel, Fig. 7.22 and Fig. 7.23).

The performances of the methods as a function of catchment elevation show a complex pattern. For the regressions the performance seems to increase with elevation, peak around 1000 m a.s.l. and then decrease. This dependence may be related to a sight decrease of aridity with elevation for the lower catchments in France and a slight increase for the higher catchments (Fig. 10.36), while in the other regions examined aridity generally decreases with elevation. The differences in the performances are therefore, again, at least partly a reflection of the differences in the hydrological characteristics in the regions they were applied. Geostatistical methods have been mainly applied to Austria (with a small number of catchments from the USA) and the slight increase in performance with elevation may be a reflection of the increasing importance of snow processes where the flow duration curves may be easier to predict than in precipitation dominated runoff regimes.

The performance of the geostatistical methods strongly increase with catchment area while index and process based methods work better for intermediate catchment sizes. Clearly, as the catchment area increases, the overlapping areas between gauged and ungauged catchments tend to be larger, so the correlations along the stream network are likely to increase which will improve the performance of the geostatistical methods. For the other methods the controls are less clear. For the smallest and largest catchments both the index and the process based methods tend to underestimate the slope of the flow duration curve. For the case of the process based methods (continuous runoff models) this is related to the calibration which has been done on the basis of minimising NSE of observed and simulated daily runoff. For that case study, the slope of the FDC was not captured well even in the calibration. This points towards the importance of carefully choosing objective functions in the calibration of runoff models in the context of the application of interest.

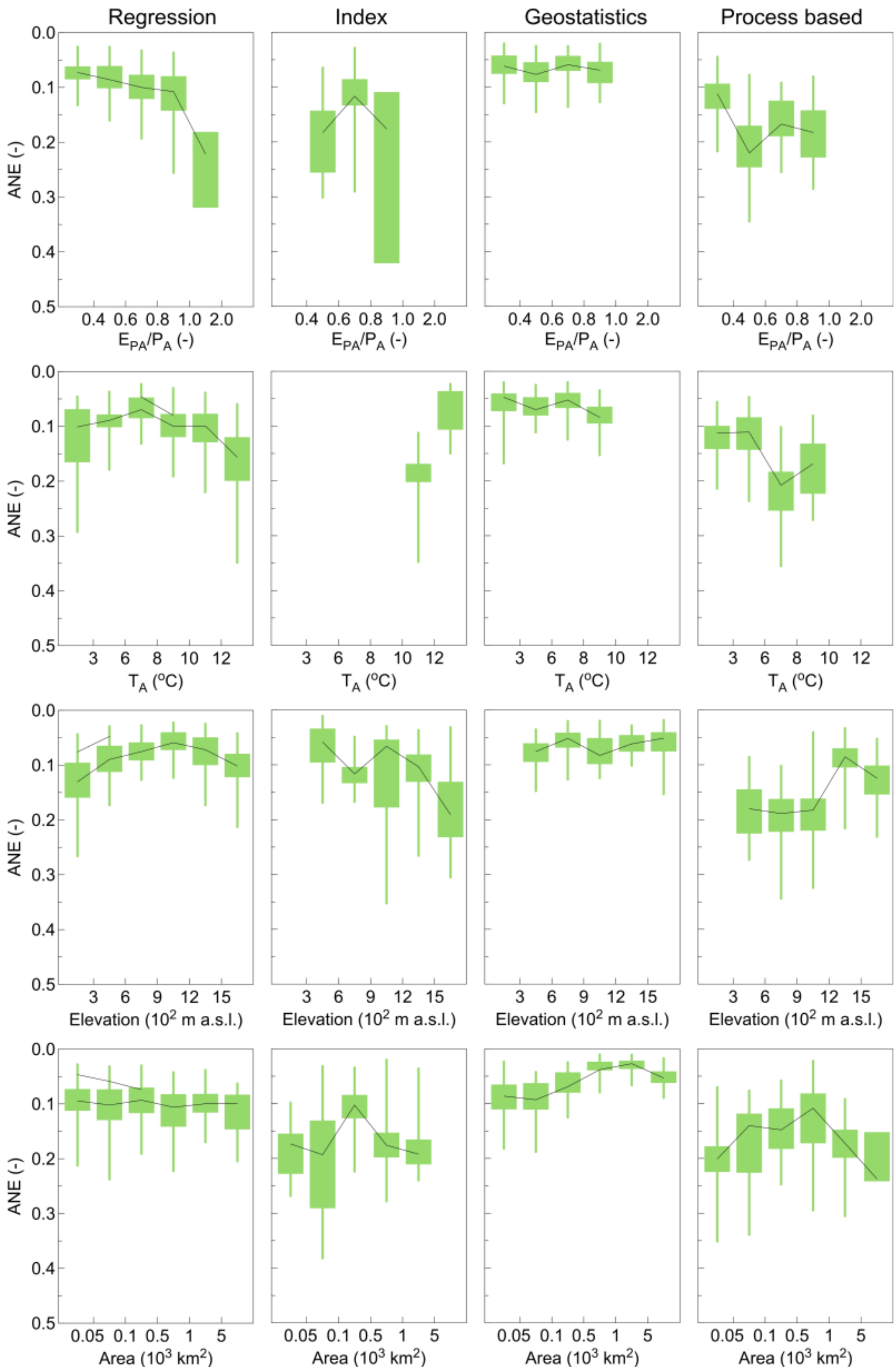

Figure 7.22 Absolute normalised error (ANE) of predicting the slopes of the FDCs in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature T_A, mean elevation and catchment area for different parameter regionalisation methods. Lines connect median efficiencies for the same study. Boxes are 40%-60% quantiles, whiskers are 20%-80% quantiles.

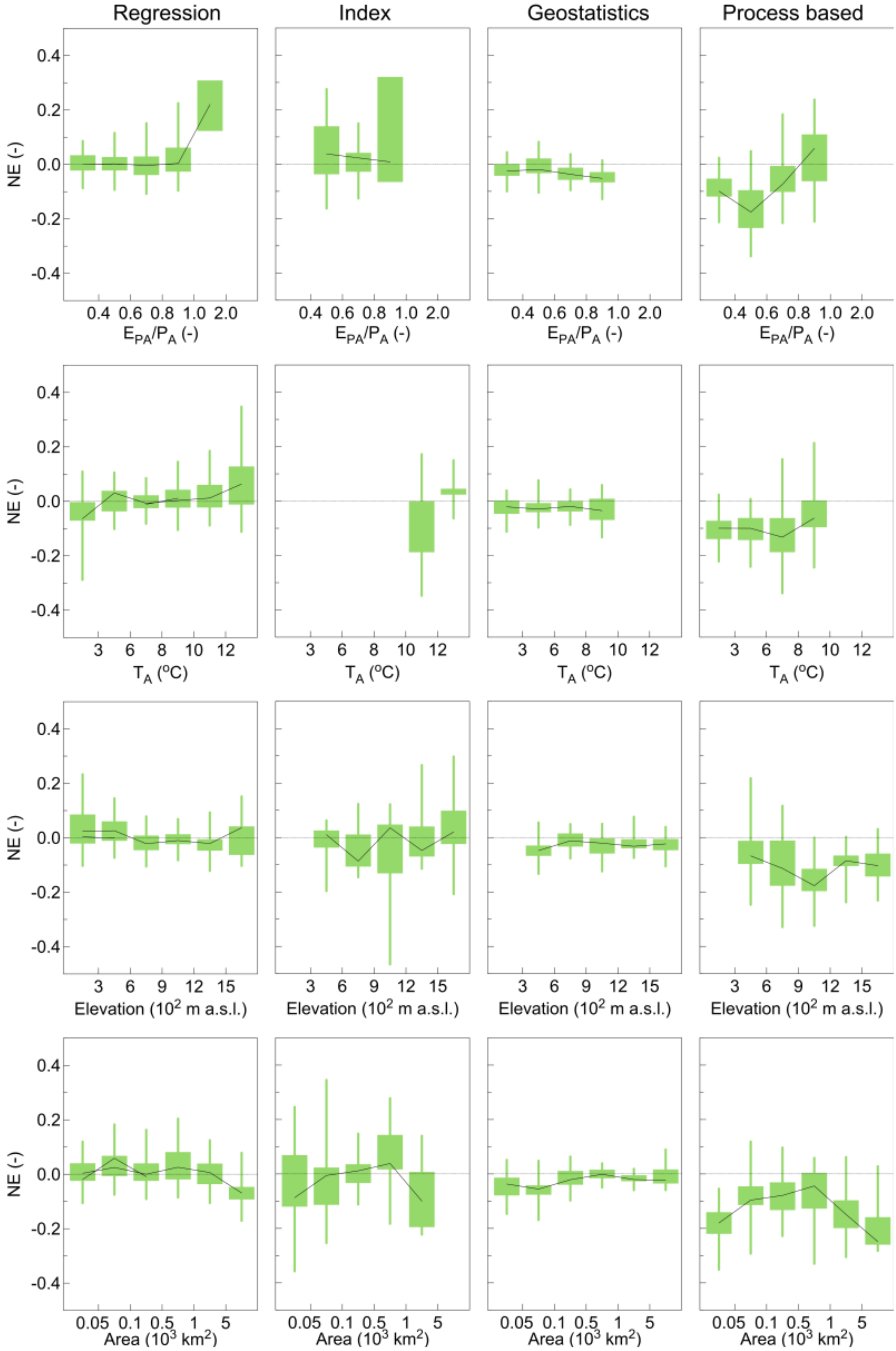

Figure 7.23 Normalised error (NE) of predicting the slopes of the FDCs in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature T_A, mean elevation and catchment area for different parameter regionalisation methods. Lines connect median efficiencies for the same study. Boxes are 40%-60% quantiles, whiskers are 20%-80% quantiles.

Which method performs best?

Fig. 7.24 summarizes the performance for different regionalisation approaches, stratified by the aridity index. The top, middle and bottom panels show the performance for all catchments of Table A7.2 marked by an asterisk, and catchments with an aridity index below and above 1, respectively. The results indicate that overall, geostatistical methods perform best, followed by the regression methods. The data sets used for the two methods were from Austria and France, respectively, which both have a relatively dense stream gauge network. The lower performance of the index method in Italy may be related to the lower stream gauge density. This is consistent with the dependence of the performance on the number of catchments in the Level 1 assessment (Fig. 7.21). There were an insufficient number of studies for a complete comparison of the methods between arid and humid catchments.

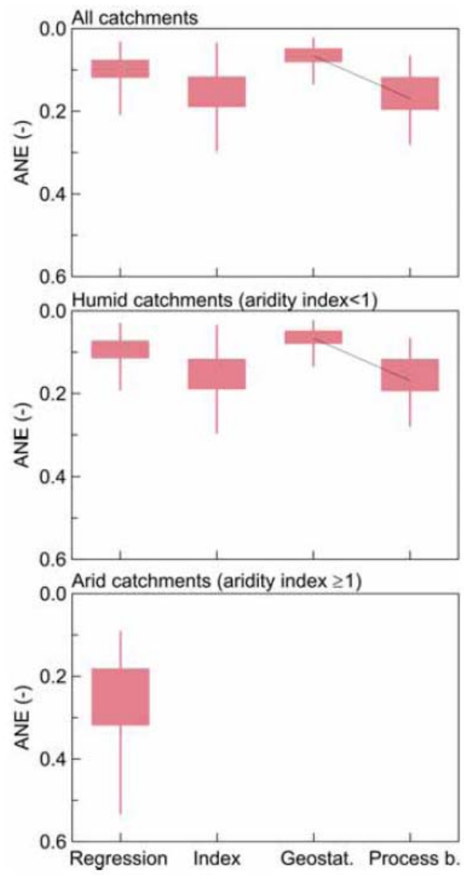

Figure 7.24 Absolute normalised error (ANE) of predicting the slopes of the FDCs in ungauged basins for different regionalisation methods, stratified by aridity. Top: all catchments. Centre: humid catchments (aridity index <1). Bottom: arid catchments (aridity index ≥1). Lines connect median efficiencies for the same study. Boxes are 40%-60% quantiles, whiskers are 20%-80% quantiles.

Main findings of Level 2 assessment:

- The performance of all methods for predicting the slope of the flow duration curve in ungauged basins decreases with increasing aridity, although the strength of decrease differs between regions.

- There is a slight tendency for the performance to decrease with air temperature. The pattern of elevation dependence is more complex and may relate to the regional patterns of aridity and snow processes.
- The performances increase with catchment size for the case of geostatistics. Scale dependencies are less clear for the other methods. The processes based methods underestimate the slope of the FDC for the smallest and largest catchments.
- Geostatistics and regression methods perform better than the other methods. This may be partly related to the higher stream gauge density of the data sets used for these methods.

7.6 Summary of key points

- The flow duration curve (FDC) is a statistical (i.e., frequency domain) representation of runoff variability at all time scales (from inter-annual variability all the way to event scale variability), and therefore it embeds within it aspects of all the other signatures studied in this book. The mean of the FDC is mean annual runoff. The seasonal flow regime smoothens out variability at both short (i.e., floods) and long (i.e., low flows) time scales; consequently the middle part of the FDC reflects runoff variability that is reflected in the seasonal flow regime.
- Similarity indices for FDC therefore include the aridity index (for annual runoff variability), geology (for low flows), storage capacity, mountain elevation and temperature (for seasonal runoff variability), and event characteristics (for floods).
- The FDC also reflects the multiplicity of pathways within the catchment that water follows and the associated time scales, and hence it connects to all of the co-evolutionary processes impacting, and impacted by, water flow processes, such as ecological, geomorphologic and pedologic processes.
- Current predictions of flow duration curves are heavily dominated by statistical methods. Geology or geology/soil related indices and topographic elevation (in mountainous regions) are, the most frequently used predictors of the slope/shape of FDCs, in addition to the aridity index, which governs the mean of the FDC.
- Process based methods are not widely used for predicting FDCs in ungauged basins; however, there is great potential for an increased use of process based methods, especially as we gain improved understanding of the underlying process controls.
- Comparative assessment of several prediction methods indicated that at least for some of the methods (e.g., regressions methods) predictive performance decreases with increasing aridity (Level 1 and 2 assessments). Predictions based on availability or collection of short records outperform regionalisation methods in humid regions, where inter-annual variability is small (Level 1 assessment), whereas this may not be the case in arid regions due to the fact that inter-annual variability is much larger, and short records are insufficient to fully capture this variability. Performance of geostatistical methods is good (Level 2 assessment). They require stream gauges in the region of interest.
- Much more insights into the FDC can be gained if the contributions of both annual runoff variability and also seasonal flow regime can be separated from the FDC, with the distribution of the residuals explored through the use of process based models, especially of the derived distribution type. Approached in this way, there is considerable scope to approach the FDCs in a comparative manner, through bringing out the differences of the FDCs between different places

(e.g., climates and landscapes), and seeking explanations for their differences using understanding of the underlying process controls.

- Considerable potential exists for a joint investigation of spatial patterns (within regions, along a river network, and between regions) of not only flow duration curves, but also associated co-evolutionary features such as hydraulic geometry, sediment stratigraphy, riparian vegetation and patterns of biodiversity of aquatic biota.

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