REGIONALISATION OF HYDROLOGIC DATA: A REVIEW

A report as part of Project D2: Regionalisation and scaling of hydrologic data

B. C. Bates

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PREFACE

The Cooperative Research Centre (CRC) for Catchment Hydrology's research program 'Flood Hydrology' has the overall objective:

> *To improve methods for estimating flood risk and the reliability of flood forecasting, and advance the understanding of catchment similarity and regional behaviour.*

The issues of catchment similarity and regional behaviour are specifically dealt with in CRC Project D2 'Regionalisation and Scaling of Hydrologic Data'.

This report by Bryson Bates from the CSIRO Division of Water Resources represents the first phase of Project D2. It provides a state of the art survey of regionalisation techniques and presents recommendations for further research, some of which will be investigated in the next phase. A review of scaling theory by other researchers within Project D2 will appear as a separate report.

The ultimate aim is to develop and test new methodologies for transferring hydrologic information from small to large areas (scaling) and from one region to another (regionalisation). This report is an important first step in achieving that goal.

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ABSTRACT

Hydrologic research within Australia has produced a large body of information derived from field experiments ranging in area from plot size to that of a small catchment. Land and water resource managers need to apply this knowledge to large river basins but existing techniques for extrapolation are incomplete and inconsistent with one another. The development of a set of coherent techniques for scaling and regionalisation would reduce the need for new and costly experiments and reduce the cost of data collection.

This report presents the results of a review of regionalisation methods as the first phase of a project to develop improved scaling and regionalisation techniques for use by Australian land and water resource management agencies. (A review of scaling theory will appear as a separate report.) The report focuses on three major areas: (1) regional flood frequency; (2) regionalisation of rainfall-runoff model parameters; and (3) low flow estimation. Two problems common to all three areas are the identification of homogeneous hydrological regions and the functional form of relationships between hydrological variables and catchment characteristics. Previous work on these issues is incomplete. Extensive work on the application of the multiscaling theory of Gupta and Waymire and the *L*-moments/index flood method of Hosking and Wallis to regional flood frequency analysis, and parameter estimation for rainfall-runoff models, is warranted.

The next phase of the project will involve the development and testing of new methodologies for regional flood frequency analysis and the regionalisation of rainfall-runoff model parameters for ungauged catchments. Issues peculiar to low flow estimation can be left for future research efforts.

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SUMMARY

This report represents the first phase of the CRC for Catchment Hydrology's Project D2, 'Regionalisation and Scaling of Hydrologic Data'. It is a review of regionalisation techniques for flood frequency, rainfall-runoff model parameters, and low flow estimation. These are the areas of most interest to practitioners.

The first part of the review examines methods for regional flood frequency analysis (RFFA). RFFA uses data from several gauged sites which have been pooled (or combined) to form a 'homogeneous' hydrological region to obtain flood quantile estimates at a site within that region. It was concluded that the application of the multiscaling theory of Gupta and Waymire and the coupled *L*-moments/index flood method of Hosking and Wallis to RFFA could be advantageous. Nevertheless, two areas deserving considerable attention are delineation of homogeneous regions and the identification of the functional form of the relationships between the index flood or flood quantiles and catchment characteristics.

The second part examines the regionalisation of rainfall-runoff model parameters. Such a regionalisation allows the estimation of design flood hydrographs for the sizing of hydraulic structures and water yield from ungauged catchments. It was concluded that further work on parameter estimation for rainfall-runoff models is warranted despite the intensive research efforts of the past. The issues of delineating homogeneous regions and identifying the functional form of the relationships between model parameters and catchment characteristics are of critical importance. Also, it is noted that the estimation of water yield from ungauged catchments is not a straight forward task since many of these catchments do not have sufficient rainfall and other climatic records for a modelling study. This problem can be addressed by the use of stochastic weather generators which provide long sequences of synthetic climatic data. However, it was found that previous work on stochastic weather generators for Australian climatic conditions is highly fragmented and incomplete. Thus further work on stochastic weather modelling is justified.

The third part examines methods for low flow estimation. In this field, regionalisation usually takes the form of regional estimation equations linking low flow measures and statistics with catchment characteristics. The information obtained from these equations is useful in reservoir design, the licensing of stream abstractions, environmental studies, and water quality management. Again, the issues of delineating homogeneous regions and identifying the functional form of the relationships between model parameters and catchment characteristics were found to be of critical importance. However, it was also noted that existing regionalisation methods often rely on the estimation of a limited number of low flow quantiles and parametric distributional assumptions. Such approaches discard valuable information on the low flow regimes of streams and further thought should be given to developing methods that preserve this information.

High priority should be given to the issues of delineating homogeneous regions and identifying the functional form of the relationships linking the index flood, flood quantiles, rainfall-runoff model parameters, and low flow measures and statistics to catchment characteristics. For this work to take place, however, it will be necessary to address the discrepancies between the index flood and multiscaling theories of regional flood frequency analysis and several issues associated with the parameter estimation in rainfall-runoff models.

1 INTRODUCTION

1·1 Purpose of Report

The purpose of this report is to ascertain the current state of research and practice in the regionalisation of hydrologic data. The report is the first phase of a project to develop and test accurate and coherent techniques for scaling and regionalisation. The next phase of the project will involve the development and testing of new methodologies for practical problems. The project is one of four under Program D of the research program of the Cooperative Research Centre for Catchment Hydrology.

The objectives of this review are:

- to survey the literature to identify the latest research developments in the regionalisation of hydrologic data;
- to compare Australian practice with these developments;
- to identify areas where further research and development are needed in the short and intermediate term, and
- to provide a useful resource to others working in the field of regionalisation.

1·2 Background

One of the most common problems in the sizing of minor hydraulic structures such as detention basins and farm dams, and the waterway areas for culverts and bridges, is the estimation of a design flood for sites at which no observed rainfall and/or runoff data are available. A popular solution to this problem is the use of regional estimation equations for deriving design flood peaks or design flood hydrographs. These equations allow the user to transfer information from a number of 'similar' gauged sites to the design site. The cost of the construction of these structures to the Australian taxpayer is of the order of $300 million per annum. A similar approach is often used by water resource planners to estimate low flow statistics for and water yield from ungauged catchments. These estimates provide useful information for reservoir design, licensing stream abstractions, environmental studies, and managing water quality.

Although regional estimation equations for a number of areas worldwide have been available for some time, there is a general awareness that these methods are incomplete, inconsistent and, in many cases, inaccurate and outdated. This must lead to unwarranted expenditures on engineering structures due to under- or over-design, and the formulation of management or planning policies that are based on questionable information.

Part of the focus of Project D2 will be on the development and testing of new technologies for regionalisation. This will include investigation of recent technologies developed overseas and the development of new methods during the course of the project. The products of this research will be in a form suitable for immediate application by practitioners. The remaining component of the project will focus on the development and use of techniques for extrapolating hydrologic data from one part of a catchment to the whole catchment. These techniques are called 'scaling' methods. This subject area will be covered in a separate report.

1.3 Structure of the Report

The report consists of three parts. The first reviews the literature on regional flood frequency analysis and the estimation of flood quantiles at ungauged sites. This is the area that has received the most attention in the literature and has many aspects in common with other types of regionalisation analyses. The second part focuses on the regionalisation of rainfall-runoff model parameter estimates. Discrete flood event models, and conceptual rainfall-runoff models that provide a continuous simulation of catchment runoff, are considered. Important secondary issues relevant to the estimation of water yield from ungauged catchments are also discussed. The third part covers low flow estimation for gauged and ungauged catchments. This area has received the least attention in the literature and is one of major importance to Australian water resource and aquatic ecosystem planners and managers.

2 REGIONAL FLOOD FREQUENCY ANALYSIS

2.1 Introduction

2.1.1 At-site flood frequency analysis

Flood frequency analysis is the study of the frequency of occurrence of high water levels in streams. Statistical methods are generally used as they acknowledge the existence of the uncertainty involved in quantifying the physical processes that determine flood magnitude. These techniques may include data-intensive methods involving the fitting of probability distributions or related quantities to flood peak discharges. They may also include the coupling of a probabilistic rainfall model with either a deterministic or a probabilistic catchment model to derive a flood frequency distribution. Here the models are usually simple enough to require little or no calibration and to allow the distribution to be derived in an analytical form [*Moughamian et al.*, 1987].

This part of the review focuses on the analysis of peak discharges. Most flood frequency techniques are based on the use of annual flood series which contain the highest instantaneous discharge recorded in each year of the record. The remainder are based on the partial flood series which is comprised of all flood peaks over a selected threshold regardless of the number of such floods occurring each year.

Let the random variable Q denote the magnitude of the largest flood discharge which occurs in a year at a given site. The probability distribution of Q can be specified by its cumulative distribution function:

$$F_Q(q) = P[Q \leq q] \qquad (2\cdot1)$$

where $F_Q(q)$ is the probability of the event that Q is at less than or equal to q.

The inverse function $q(F)$ is the quantile function of the probability distribution. It expresses the flood magnitude in terms of its nonexceedance probability F. Let Q_T denote the flood quantile of annual exceedance probability (AEP) of 1 in T (or of average recurrence interval, ARI, of T years) which is the flood magnitude which has a probability $1/T$ of being exceeded in a year. Thus

$$Q_T = q(1 - 1/T) \qquad (2\cdot2)$$

or

$$F_Q(Q_T) = 1 - 1/T \qquad (2\cdot3)$$

The objectives of flood frequency analysis are to estimate flood quantiles for a selected AEP or a range of AEPs or to estimate the AEP for a given Q. *Potter and Lettenmaier* [1990] note that there are three major problems in practice. First, the parent distribution for the quantiles is not known and cannot necessarily be assumed on theoretical grounds. Second, there is usually a lack of sufficient data to enable accurate estimation of the quantiles for the small AEPs that are of primary concern in the design of hydraulic structures. Here the quantile estimates can be quite sensitive to the assumed form of the parent distribution. Third, floods may be generated by different physical mechanisms such as snowmelt and rainfall [see, e.g., *Waylen and Woo*, 1982]. A fourth problem is that floods may be generated by different hydrologic mechanisms depending on the time history of rainfall. This can be particularly important for large, uncommon floods.

2.1.2 Regional flood frequency analysis

Regional flood frequency analysis (RFFA) uses scaled data from several gauged sites which have been pooled to form a region to obtain scaled flood quantile estimates for a hypothetical site within that region. In effect, it is an attempt to compensate for insufficient temporal characterisation of large flood behaviour by exploiting the spatial coherence of hydrological variables effectively to increase the sample size for individual sites [*Lettenmaier and Potter*, 1985; *Cunnane*, 1988; *Burn*, 1990*a*, *b*]. Another possible source of supplemental information is knowledge about large floods that occurred prior to the gauged (or systematic) flood record. *Jin and Stedinger* [1989] note that such historical information can be of value when estimating at-site flood quantiles but that its use in a regional flood frequency context is an area of dispute [see, e.g. *Hosking and Wallis*, 1986]. *Guo and Cunnane* [1991] suggest that this dispute may have resulted from the selection of different data censoring methods.

RFFA can be used to enhance the reliability of quantile estimates at gauged sites or to obtain quantile estimates at ungauged sites. In practice, the second design situation is the most common.

Potter [1987] and *Cunnane* [1988] note that the performance of all regionalisation techniques is dependent upon distributional assumptions, the degree of spatial heterogeneity, and inter-site dependence of flood data.

Some RFFA methods assume explicitly that the flood frequency behaviour of the gauge sites within the region is homogeneous with respect to relevant catchment variables. The questions of what constitutes homogeneity and how can it be best identified are problematic and have been the subject of principally statistically-based research. *Cunnane* [1988] notes that even with regionalisation techniques that make no explicit assumptions about homogeneity, it must be expected the gains in using regional rather than at-site estimation will be greater if the region of interest is homogeneous. It has also been shown that at-site estimates of flood quantiles can be preferable to estimates obtained from RFFA in the presence of extreme regional heterogeneity [*Kuczera*, 1982*a*; *Lettenmaier and Potter*, 1985]. This is particularly true for a catchment whose behaviour differs most from the 'average' catchment of the region [*Cunnane*, 1988].

The following notation and definitions will apply throughout the subsections to follow. Let $\{Q_{ij};\, i = 1, 2, \ldots, N_j;\, j = 1, 2, \ldots, M\}$ be the annual discharge maxima at M gauged sites with a total period of record given by

$$L = \sum_{j=1}^{M} N_j \tag{2·4}$$

For any site j, it is assumed that $\{Q_j, i = 1, 2, ..., N_j\}$ is a random sample from some parent population. *Cunnane* [1988] notes that most RFFA methods involve standardisation of the discharge data:

$$X_{ij} = (Q_{ij} - a_j) / b_j \qquad (2\cdot5)$$

where a_j and b_j are the location and scale statistics of the sample. Using the regional homogeneity assumption, the random variable X is assumed to have a common probability distribution with identical parameter values at all sites within the region of interest. This is an important assumption for, as *Dooge* [1986] states: '...no amount of statistical refinement can overcome the disadvantage of not knowing the frequency distribution'.

2.1.3 Index flood method

If the standardisation is of the form $X = Q/b$ where b is an index of the overall flood magnitude on a catchment, the technique is referred to as an Index Flood method. The key concept of this method is that the distributions of floods at sites within a given region are the same except for scale parameter b which reflects the size, rainfall, and runoff characteristics of each catchment. That is, it is assumed that all moments of order higher than one are identical after correction for scale. Recent work [*Smith*, 1992; *Gupta and Dawdy*, 1994; *Gupta et al.*, 1994] indicates that hydro-climatic catchment dynamics are such that the underlying premise of a regional parent distribution may be invalid even though statistical tests for more frequent floods may not cause the hypothesis to be rejected [*Kuczera*, 1982*b*]. The absence of a physically supportable, uniform general and scalable distribution would restrict severely the use of an index flood scheme. General regressions of the form used by the U.S. Geological Survey for specific AEP magnitudes [see, e.g., *Riggs*, 1973] do not come from the same parent (see Section 2.7.1).

Typically the index flood is taken as the mean of Q although any location parameter of the probability distribution can be used. *Hosking and Wallis* [1991] suggest the possible use of the median and trimmed means. *Smith* [1989] used the 90th percentile. When the index flood is the mean, $\overline{Q}$, X is a ratio of two random variables with the properties [*Greis*, 1983; *Cunnane*, 1988]:

$$E[X] = 1 \qquad (2\cdot6a)$$

$$\sigma_X = C_v(Q) \qquad (2\cdot6b)$$

$$g_X = g_Q \qquad (2\cdot6c)$$

where $E[\cdot]$ is the expectation operator, and σ, C_v, and g are the standard deviation and coefficients of variation and skewness, respectively. For small samples, the distribution of X can be quite different in form to that of $\overline{Q}$ and the variance of the mean makes a large contribution to the sampling variance of the estimated X quantiles [*Stedinger*, 1983; *Cunnane*, 1988].

Within Index Flood methods, the $X_{ij} = Q_{ij}/b_j$ are the basis for estimating X_T, the regional growth factor of AEP 1 in T or ARI of T years. The regional growth factors for different values of T define a dimensionless regional frequency distribution common to all sites in a region and hence X_T is the $100(1 - 1/T)\%$ quantile of this distribution [*Hosking and Wallis*, 1991]. It is usually assumed that the distribution of X_T is known apart from the distribution parameters θ_k ($k = 1, \ldots, p$). These parameters are estimated separately at each gauge site and combined to give regional estimates $\hat{\theta}_k^{(R)}$. *Hosking and Wallis* [1990, 1993] use a weighted average estimate:

$$\hat{\theta}_k^{(R)} = \sum_{j=1}^{M} w_j \hat{\theta}_k^{(j)} \Big/ \sum_{j=1}^{M} w_j \tag{2·7}$$

where $\hat{\theta}_k^{(j)}$ denotes the site j estimate of θ_k and $w_j = N_j$ are the weights. *Stedinger et al.* [1993] note that this choice of weights may give undue influence to those sites with much longer periods of record. They suggest that a better choice is:

$$w_j = \frac{N_j N_R}{N_j + N_R} \tag{2·8}$$

where $N_R \approx 25$. (*Stedinger et al.* [1993] note that the optimal value of N_R is dependent on the heterogeneity of the region.) The dimensionless regional frequency curve and the $\hat{\theta}_k^{(R)}$s are used to determine X_T. The $100(1 - 1/T)\%$ quantile of the flood distribution is given by

$$Q_T = X_T \overline{Q} \tag{2·9}$$

If the goal is to improve the reliability of the estimate of Q_T at gauged site j, the sample mean:

$$\overline{Q}_j = \frac{1}{N_j} \sum_{i=1}^{N_j} Q_{ij} \tag{2·10}$$

is used in (2·9). For an ungauged site within the region of interest, $\overline{Q}$ is estimated using regional information (see Section 2.7.1).

If the X_{ij} are treated as if they form a single random sample of size L from a common X parent population, the RFFA procedure is classified as a station year method [see, e.g., *Carrigan*, 1971; *Hjalmarson and Thomas*, 1992]. Here the X–T relationship of this population can be estimated from the sample by any chosen method. *Cunnane* [1988] notes that these methods may be described as a regional pooling of data as distinct from other methods which involve the regional averaging of data or the statistics of those data. Station year methods may lead to bias at large ARIs because of their failure to consider inter-site dependence; *Cunnane* [1988] cites the work of *Hosking* [1987] which suggests that this bias may not be excessive for annual flood series in England. Cunnane also notes that although regional averaging methods do not suffer bias as a result of inter-site correlation the standard error of the quantile estimates may be adversely affected by it.

2.2 Distributional Choices for At-site Quantile Estimation

While the focus of this report is the regionalisation problem it must be emphasised that an at-site estimator is a basic component of every RFFA procedure [*Potter*, 1987]. Distributional choices for at-site estimators have included the: log Pearson Type III (LP3); generalised extreme value (GEV) or one of its special cases, the extreme value types 1, 2, 3 (EV1, EV2, EV3); power normal (PN); two-component extreme value (TCEV); the generalised Pareto distribution; and Wakeby (WAK) distributions.

There is no known physical basis for choosing a flood frequency distribution. In some countries an arbitrary decision has been made to achieve uniformity between different design agencies. For example, the Institution of Engineers Australia [*IEA*, 1987] and the Interagency Advisory Committee on Water Data [*IACWD*, 1982] recommended the LP3 distribution for general use in Australia and United States, respectively. This distribution and methods for estimating its parameters have been scrutinised and criticised by many. A summary of this work prior to 1987 is given by *IEA* [1987] and need not be repeated here. Work since the mid 1980s has indicated that reassessment of the use of the LP3 distribution for practical flood design is overdue [*Wallis and Wood*, 1985; *Potter and Lettenmaier*, 1990].

Lesser known are the TCEV and PN distributions. *Waylen and Woo* [1982] and *Rossi et al.* [1984] have proposed the four-parameter TCEV distribution for modelling annual flood series. They assumed that annual flood series arise from two independently distributed EV1 components representing two different storm mechanisms that give rise to different flood characteristics. (Thus the cumulative distribution function for the TCEV distribution is defined by the product of two EV1 cumulative distribution functions.) The TCEV distribution has been successfully applied to Canadian data [*Waylen and Woo*, 1982], Italian data [*Rossi et al.*, 1984], and United Kingdom data [*Beran et al.*, 1986]. The PN distribution was suggested for use in flood frequency analysis by *Chander et al.* [1978]. This approach applies the one-parameter power transformation proposed by *Box and Cox* [1964] to the annual flood series and assumes that the transformed series is independently and normally distributed. It has been successfully applied to Australian data [*Kuczera*, 1983*a*; *Ashkanasy*, 1985].

Smith [1987] proposed a generalised Pareto procedure for estimating the quantiles of the upper tail of the annual flood series and applied it to a data set from the Potomac River. Smith used only the largest 10-20% of the flood peaks. He found that severe censoring yields very different quantile estimates from those obtained from moderate censoring. Standard errors of quantile estimates for ARIs of the order of 1,000 to 10,000 years were of the same order of magnitude as the estimates, suggesting that these estimates are of no value.

The distributions that have aroused the most interest as possible alternatives to the LP3 are the GEV and WAK distributions. The Natural Environment Research Council [*NERC*, 1975] has endorsed the GEV distribution for flood frequency analyses in the United Kingdom. *Houghton* [1978] introduced the five-parameter WAK distribution which has the ability to mimic the behaviour of most of the conventional distributions used in hydrology. Both distributions have been found to perform well when compared with other candidates [e.g., *Hosking et al.*, 1985*a*; *Wallis and Wood*, 1985; *Lettenmaier et al.*, 1987; *Arnell and Gabriele*, 1988; *Potter and Lettenmaier*, 1990]. While the performance of the WAK distribution appears to be remarkable given its lack of parsimony of parameters, it is only useful in regional rather than at-site applications.

The WAK and TCEV distributions can capture some of the separation effect observed by *Matalas et al.* [1975]. This effect refers to the differences which may appear between samples of synthetic and natural streamflow data when the standard deviation of skew is plotted against the mean skew for regional data. Generally, the natural data display a larger standard deviation of skew than the synthetic data suggesting that real skews are larger than those of most conventional distributions. Work by Dawdy and Gupta [D.R. Dawdy, pers. comm., 1994] shows that this 'separation' may be an artefact of earlier non-physics based statistical analysis.

Adamowski [1985, 1989] and *Adamowski and Feluch* [1990] have advocated the use of nonparametric density estimation. This approach removes the need for a priori selection of a probability density function and can produce a better fit to observed flood data with a highly skewed density and a long upper tail than parametric methods. However, it implies a very small probability in extrapolation beyond the largest gauged flood. The use of nonparametric methods appears to have attracted little attention elsewhere.

2.3 Regional Homogeneity

2.3.1 General concepts

Many RFFA methods entail the pooling of data from gauged sites within a defined physical region. The definition of this region depends on which aspect of the behaviour of flood frequency is considered to be homogeneous. *Potter* [1987] states that this is the greatest challenge in applying regionalisation techniques since it requires the ability to discern whether anomalous flood statistics are due to sampling variability or to population differences caused by floods that do not conform with the assumed distribution.

Gabriele and Arnell [1991] note that while the accuracy of a regionalisation approach will decline as regional heterogeneity increases, the performance of regional estimators will also decline as the size of the region is decreased. There does not appear to be any work on the minimum number of stations that is required to define a region adequately and the tolerable level of associated variations in at-site record lengths. However, the Monte Carlo experiments of *Hosking and Wallis* [1988] suggest that as the number of sites M within a region is increased, there comes a point after which further increases in M yield little improvement in the accuracy of quantile estimates. This point is reached more quickly when inter-site dependence is present. Overall, there appears to be little improvement for $M > 20$.

Little of the published literature examines the physical causes for changes in apparent flood populations in a geographic region. *Wolff and Burges* [1994] have demonstrated the subtle influence that a relatively short reach of river channel and floodplain may have on populations of flood peaks as flood hydrographs propagate down the channel. The population for an upstream gauge is different to that at a downstream location in the same catchment. This suggests that the location within a catchment of the gauged site is important when the data are used in a regional statistical scheme.

Cunnane [1988] states that the identification of homogeneous regions is necessarily based on statistical methods and that the ability of these methods to assign sites to regions or to detect unusual sites within a region is low. He attributes this to the moderate amounts of flood frequency data that are available. Data limitations (quantity and quality) also affect other types of hydrological regionalisation (e.g., the regionalisation of rainfall-runoff parameters).

2.3.2 Classification techniques and tests for regional homogeneity

The classification techniques that have been used to delineate homogeneous hydrological regions include:

- analysis of regression residuals [e.g., *NERC*, 1975; *Tasker* 1982*a*];
- cluster analysis [e.g., *Mosley*, 1981; *Tasker*, 1982*b*; *Acreman and Sinclair*, 1986; *Wiltshire*, 1986; *Burn*, 1989; *Hughes and James*, 1989; *Roald*, 1989; *Nathan and McMahon*, 1990; *Burn and Boorman*, 1993];
- principal component analysis [e.g., *Blake et al.*, 1970; *Hawley and McCuen*, 1982; *Burn*, 1988; *Nathan and McMahon*, 1990];
- principal co-ordinate analysis [e.g., *Hughes*, 1987; *Laut et al.*, 1983; *Cook et al.*, 1988];
- factor analysis [e.g., *Abrahams*, 1972; *White*, 1975];
- canonical correlation analysis [e.g., *Decoursey*, 1973; *Cavadias*, 1990];
- discriminant analysis [e.g., *Decoursey*, 1973; *Waylen and Woo*, 1984]; and
- analysis of shapes of probability density functions [*Gingras and Adamowski*, 1993].

None of these statistical methods is inherently superior to its competitors and each has subjective elements and limitations. For example, the method of residuals depends highly on selection of the regression model and explanatory variables. Errors in these selection processes can be difficult to detect even when using the strongest multiple linear regression tools [see, e.g., *Bates and Sumner*, 1991]. Similarly, most clustering techniques make implicit or subjective assumptions about the type of structure present in the data. They depend also on measurement scale.

An important consideration is whether regions should be constrained to be geographically contiguous. In many areas of Australia, the number of gauged sites is so small that the delineation of hydrologic regions would be counterproductive and resort is made to geographically contiguous regions [*IEA*, 1987]. Some formal classification techniques, such as the method of residuals, are also based on the assumption that an ungauged site will be assigned to the geographical region in which it lies. In the context of the relatively benign hydrology of England, *Wiltshire* [1985, 1986] notes that: (1) geographical proximity may not be a useful indicator of hydrologic similarity; (2) the distance between sites is not a measure of dissimilarity; (3) flood series within geographically contiguous regions are less likely to be independent; and (4) such regions engender abrupt changes in the values of hydrological parameters at their boundaries.

Acreman and Wiltshire [1989] proposed the 'region of influence' (ROI) approach in which each site can be assigned its own unique region consisting of sites with which it is 'similar' and a fractional membership to more than one region. There is no need to draw boundaries between regions or for all sites in a particular area to use the same number of gauged sites in the estimation of at-site flood quantiles [*Burn*, 1990*a*, *b*]. Similarity is judged using the assumption that catchments with similar flood frequency distributions should have similar values of catchment characteristics [*Hosking and Wallis*, 1990]. A hydro-geomorphic-climatological basis for discerning similarity has not yet been established. A disadvantage with this approach is that a new analysis has to be made for each new ungauged site to find the set of sites that form its region. Given the lack of guidance provided by statistical methods, there remains a need for developing relevant hydrologic laws that would permit the classification of catchments [see *Dooge*, 1986].

There have been few studies to compare the relative merits of classification techniques. *Bhaskar and O'Connor* [1989] compared the method of residuals with a procedure based on cluster and discriminant analyses using data from 253 sites across Kentucky. The clustering variables used were $C_v(Z)$ where $Z = \log Q$ and the specific mean annual flood $\overline{q}_s = \overline{Q} / A$ where A is catchment area. The variables used to discriminate between 'cluster regions' were catchment area, basin shape index, main channel slope, and main channel sinuosity. *Bhaskar and O'Connor* [1989] found that the regions obtained from cluster analysis were different to those obtained from the method of residuals and were not coincident with geographical boundaries. The 'cluster regions' were also more distinguishable and better discriminated than those obtained from the method of residuals in that the total percentage of correct classifications were 64·8% and 16·9%, respectively. *Burn* [1990*a*, *b*] compared a ROI approach with a regionalisation approach based on principal component analysis and fixed regions that had been used previously [*Burn*, 1988]. He found that while both methods produced comparable results for sites with 'average' $C_v(Q)$ and $\overline{q}_s$ values, the ROI approach results in a set of sites with a closer concordance with the target site and flood quantile estimates that are more accurate than those obtained from the regionalisation technique. Through a Monte Carlo experiment, *Burn* [1990*b*] found that the network average root mean squared errors for flood quantiles estimated using the ROI approach were about 70% of those obtained by using all sites in the estimation of at-site extremes or a partitioning of the stations into three regions identified by a clustering approach. All three methods gave comparable results for average bias.

Several tests have been proposed for checking whether marked homogeneity exists within the groups and whether the groups are significantly different from each other. *Dalrymple* [1960] compared the variability of estimates of X_{10} for each site within a region with the expected variability if sampling error alone was responsible for the differences between sites. An underlying EV1 distribution was assumed. *Mosley* [1981], *Tasker* [1982*b*] and *Bhaskar and O'Connor* [1989] used discriminant analysis to test the effectiveness of groupings. *Wiltshire* [1986] proposed two tests based on the C_v of the annual flood series alone but suggested that additional statistics such as the coefficient of skewness could be imbedded in the procedure. *Acreman and Sinclair* [1986] used a likelihood ratio test based on the assumption of an underlying GEV distribution. The power of this test is low for short record lengths. *Nathan* *and McMahon* [1990] used *Andrews'* [1972] curves to test for homogeneity. These curves represent an n–dimensional variable as a two-dimensional curve and can be used for the identification of clusters and atypical values in the data. A plot of the curves for similar catchments appears as a closely-spaced band. *Hosking and Wallis* [1993] have devised tests based on L-moments which are described in a later Section. *Nathan and Weinmann* [1991] examined the use of L-moment ratio plots.

2.3.3 Importance of regional homogeneity

The importance of grouping sites into statistically, and presumed physically, homogeneous regions for regional estimation has been addressed using both Bayesian (subjective) and classical (frequentist) statistics. Using an empirical Bayes, normal probability model, *Kuczera* [1983*b*] showed that the pooling of at-site and regional data could be counterproductive at an atypical site depending on the ratio of the difference between the site and regional quantile estimates to their expected differences. *Lettenmaier and Potter* [1985] and *Lettenmaier et al.* [1987] conducted Monte Carlo experiments to explore the influence of heterogeneity (modelled by variations in the second moment) on RFFA methods. Both studies showed that the performance of the regional estimators deteriorated as either the regional mean or median C_v, $M(C_v)$, or the site-to-site variation in C_v, ($C_v(C_v)$ or $R^*(C_v) = R(C_v)/ M(C_v)$ where $R(C_v)$ denotes the regional range in C_v), increased. (Note that the latter result is not surprising for the simple index flood methods that were tested.) It was also found that large biases can result if the distributional form is misspecified and that the use of alternative methods which accommodate regional heterogeneity in moments higher than the first order may be advantageous. Overall, small departures from perfect homogeneity ($C_v(C_v) < 0{\cdot}05$, say) were not found to have an appreciable effect on RFFA. However, the question remains: what does one do when larger variability is present?

2.4 Inter-Site Dependence

Cunnane [1988] lists three factors which may lead to the magnitudes of annual flood series at different sites within the same region exhibiting some association or dependence:

- in some years of the record, the annual maxima at a number of sites may be due to the same meteorological events;
- during a relatively dry spell, all or most of the annual maxima may be low over the region but not necessarily due to the same set of meteorological events; and
- a persistent absence of large or extreme precipitation in widespread meteorological events leading to moderate annual maxima at all or most sites. This also may be caused by different meteorological events.

Cunnane [1988] notes that some RFFA methods make use of inter-site dependence (or correlation) explicitly while others depend on its complete or partial absence. The effects of inter-site dependence on RFFA have attracted limited attention. Using his empirical Bayes, normal probability model and a first-order analysis, *Kuczera* [1983*b*] found inter-site correlation to be of secondary importance when compared with the effects of spatial heterogeneity. *Stedinger* [1983] described a regionalisation approach based on a log-space transformation and derived theoretical limits on estimator accuracy which arise when concurrent flows at gauged sites are correlated. He found that in the presence of reasonable average cross-correlation ($\overline{\rho} > 0{\cdot}3$) there are severe limits on the accuracy of estimates of regional statistics when the length of the concurrent record is short. *Hosking and Wallis* [1988] conducted Monte Carlo experiments to assess the effects of inter-site dependence on the regional probability weighted moments (PWM) algorithm. (A brief description of PWM and the recently developed *L*-moments is given below.) Hosking and Wallis confirmed Kuczera's findings, but also found that any bias in the flood quantiles is unchanged by the presence of inter-site dependence and that RFFA is more accurate than at-site analysis when both spatial heterogeneity and inter-site dependence are present and the probability distribution is misspecified. *Stedinger's* [1983] theoretical limits were found by *Hosking and Wallis* [1988] to over-estimate the root-mean-square error of the regional growth factor.

2.5 Effects of Measurement Errors on Flood Frequency Analysis

The accuracy of estimated peak discharge rates depends upon flood magnitude. Peak stages of low magnitude floods are recorded at the gauging station and the corresponding discharge read from a rating curve established by current meter measurements. Peak discharges for intermediate magnitude floods are usually inferred by extrapolating the rating curve. For high magnitude floods, peak stages may be inferred from high water marks and the discharge computed by indirect means such as the slope-area method. Thus the largest events in a typical annual flood series may contain considerable measurement errors [*Jarrett*, 1987; *Kirby*, 1987] and the variances of peak discharge estimates may vary with stage [*Potter and Walker*, 1981]. These events can have an disproportionate influence on extreme quantile estimation, particularly for heavy-tailed probability distributions such as the LP3 distribution in the case of large positive skew [*Greis*, 1983].

Potter and Walker [1981] investigated the effects of this type of error, assuming that both measurement methods were unbiased and that the use of indirect flow rate estimation methods led to a large increase in the standard deviation of the measurement error. They found that in the presence of this type of error the coefficients of variation, skewness, and kurtosis of the distribution of measured flood discharges are significantly higher than those of the parent distribution (which was assumed to be log normal, LN). In a later study where they examined the small-sample aspects of this error, *Potter and Walker* [1982] found that the effect of this error was to offset the bias due to the small-sample boundedness of these statistics [see, e.g., *Kirby*, 1974; *Samuelson*, 1968; *Wallis et al.*, 1974] and that the bias due to the error increased with sample size.

Cong and Xu [1987] presented an alternative analysis of the problem based on the LP3 distribution, Chinese gauging practice and data. They found that in the absence of extremely large floods, the effects of small measurement errors are themselves small and suggested that they could be neglected. However Cong and Xu qualified their findings by stating that it is not usually necessary to extrapolate established rating curves for middle to large sized Chinese rivers. Thus the effects of measurement error may be more pronounced in situations where considerable extrapolation is needed.

2.6 Regional Flood Frequency Analysis for Gauged Sites

RFFA methods which use both data for the site of interest and data from other sites in the same region include:

- Institutionalised methods such as those of the U.S. Geological Survey, the Interagency Advisory Committee on Water Data (IACWD, formerly the United States Water Resources Council), and the Natural Environment Research Council (NERC);

- Bayesian methods;

- Two-component extreme value (TCEV) method;

- methods based on *L*-moments; and

- threshold methods.

2.6.1 Institutionalised methods

The Interagency Advisory Committee on Water Data [*IACWD*, 1982] method involves the use of a LP3 distribution. The first two moments of *Z* are estimated from at-site data by the method of moments while the coefficient of skewness is estimated jointly from at-site and regional data. The rationale is that at-site records are not typically long enough to give an accurate estimate of the skewness of *Z*. Thus the accuracy of the estimated skew coefficient is improved by weighting the at-site skew $\hat{g}_Z$ and a generalised (regional) skew $\overline{g}$ estimated by pooling information from nearby sites or interpolating on the published map of $\overline{g}$ for the United States. Here the weighting of the at-site and generalised skew is in inverse proportion to their individual mean-square errors:

$$g_w = \frac{MSE_{\overline{g}}(\hat{g}_Z) + MSE_{\hat{g}_z}(\overline{g})}{MSE_{\overline{g}} + MSE_{\hat{g}_z}} \tag{2·11}$$

where g_w is the weighted skew coefficient, and $MSE_{\hat{g}_z}$ and $MSE_{\overline{g}}$ are the mean-square errors of at-site and generalised skew, respectively. *IACWD* [1982] recommend using $MSE_{\overline{g}} = 0 \cdot 302$ if $\overline{g}$ is obtained from the published map. If *Z* is LP3 distributed:

$$MSE_{\hat{g}_z} \approx 10^{\{a-b[\log_{10}(N/10)]\}} \tag{2·12}$$

where

$$a = \begin{cases} -0 \cdot 33 + 0 \cdot 08|\hat{g}|, & |\hat{g}| \le 0 \cdot 90 \\ -0 \cdot 52 + 0 \cdot 30|\hat{g}|, & |\hat{g}| > 0 \cdot 90 \end{cases} \tag{2·13}$$

$$b = \begin{cases} 0 \cdot 94 - 0 \cdot 26 |\hat{g}|, & |\hat{g}| \leq 1 \cdot 50 \\ 0 \cdot 55, & |\hat{g}| > 1 \cdot 50 \end{cases} \tag{2·14}$$

and N is the record length in years.

Tasker and Stedinger [1986] presented an improved weighted least squares method for estimating the generalised skewness and its standard error. This method results in an estimate of standard error which is not inflated by sampling variability. Using Monte Carlo simulation, *Wallis and Wood* [1985] found that procedures based on the concept of a generalised coefficient of skewness can improve the accuracy of flood quantile estimates. However, they also found that the GEV-PWM and WAK-PWM procedures performed significantly better. These findings were later supported by the results of the Monte Carlo experiments of *Potter and Lettenmaier* [1990].

The Natural Environment Research Council [*NERC*, 1975] method consisted of a mixture of regional pooling and across station averaging. It is based on the GEV distribution and a subjective, graphical procedure involving the drawing of the X–T curve with less weight being given to ordinates with large T than to those with moderate T. This weighting scheme can be carried out objectively by using a least squares algorithm. However, *Hosking et al.* [1985*a*] found a least squares implementation of the method to be less efficient and more biased than GEV-PWM and WAK-PWM procedures.

2.6.2 Bayesian methods

Bayesian methods offer a means of combining at-site and regional information without resort to reduced or standardised flood series or to the assumption of regional homogeneity. Regional information about the distribution parameters is expressed as a prior distribution conditional on catchment characteristics. Using Bayes theorem, this information is combined with at-site data expressed as a sample likelihood to give a posterior distribution of the distribution parameters. Flood quantile estimates at the site are then obtained from the posterior distribution. *Cunnane and Nash* [1974] and *Cunnane* [1988] describe the Bayesian approach to RFFA.

Kuczera [1982*b*] described the application of empirical Bayes (EB) theory to RFFA and presented a special case, the linear empirical Bayes (LEB) approach. Using a case study in which floods were assumed to be log normally distributed and sites had record lengths of 10 and 30 years each, he demonstrated that EB techniques offer better performance over at-site procedures in estimating the 1 in 100 AEP flood. The difference was more marked for the shorter record lengths. The prior distribution is influential typically up to a sample size of about 20 to 25. For larger sample sizes, the sample likelihood dominates and the prior distribution has little influence.

Prior distributions can be obtained from regression relations between the distribution parameters and catchment characteristics. However, these distributions are usually imprecise and do not improve the precision of the at-site estimates [*Cunnane*, 1988]. *Lettenmaier and Potter* [1985] compared and index flood estimators in a Monte Carlo simulation study. Overall, they found that the LEB quantile estimates where not as precise as estimates obtained from index flood methods.

Kuczera [1983*a*] presented an EB procedure for the regionalisation of the shape parameter of the power normal (PN) distribution. The PN distribution uses the power transformation proposed by *Box and Cox* [1964]:

$$X = \begin{cases} (Q^{\lambda} - 1) / \lambda, & \lambda \neq 0, \quad Q > 0 \\ \ln Q, & \lambda = 0, \quad Q > 0 \end{cases} \tag{2·15}$$

where λ is the transformation (shape) parameter and X is assumed to be independently and normally distributed $N(\mu, \sigma^2)$. When $\lambda = 0$, the PN reduces to the LN distribution.

The outcomes of *Kuczera's* [1983*a*] method are the posterior distributions of the PN parameters μ, σ and λ, and the flood quantiles. The prior distribution of λ includes the effects of unequal sampling variances between sites and inter-site correlation.

2.6.3 Two-component extreme value (TCEV) method

Rossi et al. [1984] developed a station year method based on the TCEV distribution. Estimates of the four distributional parameters were obtained by the method of maximum likelihood. However, they recommended that the TCEV distribution be used in a regional rather than an at-site estimation context as its use can lead to unstable parameter estimates.

Beran et al. [1986] derived expressions for the moments of the TCEV distribution including PWM. *Arnell and Gabriele* [1988] conducted Monte Carlo experiments to examine the performance of the regional TCEV flood frequency estimation procedure [*Rossi et al.*, 1984; *Fiorentino et al.*, 1985; *Rossi et al.*, 1986; *Fiorentino et al.*, 1987] and to compare it with two other methods based on the generalised extreme value (GEV) and Wakeby (WAK) distributions. The regional GEV and WAK parameters were estimated using PWM. They found that there were occasions when the TCEV procedure failed to reach a solution, the procedure is robust in the sense that its worst efforts were not as bad as those of the GEV-PWM and WAK-PWM methods, and that the performance of the procedure declines as sample sizes decrease from 40 to 10.

RFFA approaches based on the four parameter TCEV and five parameter WAK distributions provide a means of fitting a theoretical distribution to all of the flood data. In most applications a distribution that describes the largest floods is required. The relatively parsimonious three parameter GEV distribution has been used for this purpose.

Gabriele and Arnell [1991] proposed a hierarchical approach based on the TCEV and GEV distributions which accounts for different spatial variability in different flood characteristics, and which attempts to maximise the benefits of pooling data while minimising the adverse effects of defining too large a region. They use information from larger regions (i.e., more sites) to estimate the distributional parameters controlling skewness than are used to derive the parameters that determine the coefficient of variation. Simulation experiments based on the experimental design used by *Lettenmaier et al.* [1987] revealed that the subdivision of regions with assumed constant skewness into regions with assumed constant coefficient of variation can lead to more precise quantile estimates. (*Ribeiro-Correa and Rousselle* [1993] have proposed a hierarchical and empirical Bayes approach for fitting regional Pearson Type III distributions.)

2.6.4 Methods based on *L*-moments

Theory. Traditional methods of parameter estimation for flood frequency distributions include the method of moments and maximum likelihood estimation. *Greenwood et al.* [1979] introduced the concept of probability weighted moments (PWM) of a random variable Y which are defined as

$$M_{p,r,s} = E\left[Y^p (F_Y(y))^r (1 - F_Y(y))^s\right] \tag{2·16}$$

where p, r, s are real numbers. If $r = s = 0$, (2·16) represents the conventional moment about the origin of order p. *Cunnane* [1988] notes that PWM calculations can be performed first in the Q-domain followed by standardisation, or in the X-domain after standardisation of the Q values. Direct application of the PWM method is restricted to distributions that are expressible directly in inverse form. *Greenwood et al.* [1979] present explicit expressions for the parameters of the WAK, generalised lambda, kappa, Weibull, and Gumbel distributions as functions of PWMs. *Hosking et al.* [1985*b*] present PWM estimators of the parameters of the GEV distribution. The LP3 distribution is not overly tractable. *Song and Ding* [1988] and *Ding et al.* [1989] propose an iterative PWM method for estimating the parameters of the Pearson Type III distribution. *Jakubowski* [1992] presents the fundamental formulae for the PWM estimators for this distribution in which the estimator of the shape parameter is an implicit function of that parameter and PWMs.

Several index flood studies in which distributions are fitted to the annual flood series using PWM have appeared in the literature [*Wallis*, 1980; *Greis and Wood*, 1981; *Hosking et al.*, 1985*a*; *Lettenmaier and Potter*, 1985; *Wallis and Wood*, 1985; *Lettenmaier et al.*, 1987; *Potter and Lettenmaier*, 1990]. Distributional choices have included EV1, EV2, EV3, GEV, and WAK distributions [Potter, 1987]. These methods have been found to perform very well in a variety of situations and to be vastly superior to existing institutionalised methods (see above).

An alternative to conventional descriptions of a distributions shape such as the coefficients of variation, skewness and kurtosis is *L*-moments. *Hosking* [1990] defined *L*-moments by:

$$\lambda_r = E\left[Y P^*_{r-1} F_Y(y)\right] \tag{2·17}$$

where $P_r^*(.)$ denotes the rth shifted Legendre polynomial. *L*-moments and PWM are related by

$$\lambda_{r+1} = \sum_{k=0}^{r} p^*_{r,k} \beta_k \tag{2·18}$$

where

$$\beta_k = M_{1,k,0} \tag{2·19}$$

and

$$p^*_{r,k} = (-1)^{r-k}\binom{r}{k}\binom{r+k}{k} \tag{2·20}$$

Thus procedures based on PWM and L-moments are equivalent. Let $y_1 \le y_2 \le \ldots \le y_n$ be a finite ordered sample. Then an unbiased estimator of λ_r is given by

$$\hat{\lambda}_r = \sum_{k=0}^{r} p^*_{r,k}\, b_k \tag{2·21}$$

where

$$b_k = n^{-1}\sum_{j=1}^{n} \frac{(j-1)(j-2)\ldots(j-r)}{(n-1)(n-2)\ldots(n-r)}\, y_j \tag{2·22}$$

Useful quantities are the L-moment ratios:

$$\tau = \lambda_2 / \lambda_1 \tag{2·23a}$$

$$\tau_r = \lambda_r / \lambda_2 \qquad r = 3, 4, \ldots \tag{2·23b}$$

where $|\tau_r| < 1$. The estimator of τ is consistent but not unbiased.

The advantage that L-moments has over PWM is that the ratios defined by (2·23*a*, *b*) are dimensionless and are more easily interpretable as measures of distributional shape. *Hosking and Wallis* [1993] note that: λ_1 is the mean of the distribution (a measure of location); λ_2 is a measure of scale; τ is a L-moment coefficient of variation (L CV); τ_3 a measure of skewness (L skewness); and τ_4 a measure of kurtosis (L kurtosis). Thus the distributional parameters are taken as $\lambda_1, \tau, \tau_3, \ldots, \tau_p$.

The estimators of λ_1, λ_2 and particularly τ_3 and τ_4 are used to identify implausible parent distributions and to estimate the parameters by equating the estimates to expressions for the corresponding population L-moments [*Hosking*, 1990]. L-moments are more robust than conventional moments to extremes in the data which are important hydrologically and yield more efficient parameter estimates than the maximum likelihood method.

Data screening and identification of homogeneous regions. *Hosking and Wallis* [1993] have devised tests based on L-moments for identifying unusual sites within a region and for assessing whether a proposed region is homogeneous. Let $\boldsymbol{u}_j = (\tau^{(j)}, \tau_3^{(j)}, \tau_4^{(j)})^{\mathrm{T}}$ be the L-moment ratio vector for site j. The first test is based on a discordancy measure:

$$D_j = \frac{1}{3}\left(\boldsymbol{u}_j - \bar{\boldsymbol{u}}\right)^{\mathrm{T}} S^{-1}\left(\boldsymbol{u}_j - \bar{\boldsymbol{u}}\right) \tag{2·24}$$

where

$$\bar{u} = \frac{1}{M}\sum_{j=1}^{M} u_j \tag{2·25}$$

and

$$S = \frac{1}{M-1}\sum_{j=1}^{M}\left(u_j - \bar{u}\right)\left(u_j - \bar{u}\right)^{\mathrm{T}} \tag{2·26}$$

While *Hosking and Wallis* [1993] suggest $D_j \geq 3$ as a criterion for declaring a site to be unusual, they recommend that the data for sites with the largest D_j values should be scrutinised carefully regardless of the magnitude of these values. The second test is based on a heterogeneity measure which is determined by a five stage process: (1) compute the weighted standard deviation of the at-site sample *L* CVs defined by

$$V = \sum_{j=1}^{M} N_j \left(\tau^{(j)} - \bar{\tau}\right)^2 \Big/ \sum_{j=1}^{M} N_j \tag{2·27}$$

(2) fit the four parameter kappa distribution to the group average *L*-moments; (3) generate a large number N_{sim} of homogeneous regions from the fitted distribution so that the simulated regions have no cross or serial correlation and the record lengths of the *M* sites are preserved; (4) compute *V* for each simulated region and the mean μ_V and standard deviation σ_V of the N_{sim} values of *V*; and (5) compute the heterogeneity measure defined by

$$H = \frac{\left(V - \mu_V\right)}{\sigma_V} \tag{2·28}$$

Hosking and Wallis [1993] suggest $N_{\mathrm{sim}} = 500$ and that a region be declared 'acceptably homogeneous' if $H < 1$, 'possibly homogeneous' if $1 \leq H < 2$ and 'definitely heterogeneous' if $H \geq 2$. Hosking and Wallis note that it may not be possible to fit the kappa distribution to regional average *L*-moments if $\bar{\tau}_4 >> \bar{\tau}_3$. In such cases they recommend that the simulated regions be generated from a fitted generalised logistic distribution.

2.6.5 Threshold methods

Cunnane [1988] notes that threshold methods may refer to censored annual maximum series or to peaks over the threshold (POT) series. (The latter is also known as partial duration series.) Threshold methods contribute little if any information on low AEP floods ($T > 10$) that is not contained in the annual series. The convergence of threshold and annual flood series was demonstrated by *Langbein* [1949]. Consequently threshold methods are not considered any further.

2.7 Application of Regional Flood Frequency Methods at Ungauged Sites

Two general techniques that have been used to derive quantile estimates at ungauged sites are hydrologic regressions and derived flood frequency distributions. These techniques are also useful in situations where there are few flow data available at or near the site of interest.

2.7.1 Hydrologic regression

Regression can be used to derive empirical equations for the prediction of standardised or unstandardised flood quantiles for an ungauged catchment. A regression is developed for a region that is thought to be homogeneous with respect to flood peaks. The index floods or flood quantiles for the gauged sites within the region are related to independent variables in the form of measurable climatic characteristics (usually rainfall volume) and physical features (such as drainage area). Values of these independent variables for the ungauged catchment are used in the regression equation to estimate the required index flood or flood quantile.

The most commonly adopted method for estimating the parameters of the regression models for RFFA has been ordinary least squares (OLS). OLS is predicated on the assumptions that the regression residuals have zero mean and constant variance, and are independently distributed. However, *Stedinger and Tasker* [1985] show that these assumptions are likely to be violated because of site-to-site variations in the record length at gauged sites and cross correlations among concurrent discharges. They developed procedures for using weighted least squares (WLS) and generalised least squares (GLS) which account for heteroscedastic residuals (residuals with a nonconstant error variance across the range of computed flood quantiles), and both heteroscedastic residuals and inter-site correlation, respectively. Using Monte Carlo experiments, *Stedinger and Tasker* [1985, 1986] showed that GLS provides more accurate parameter estimates, improvements in the precision of the estimates, and an almost unbiased estimator of the underlying regression model's error variance than OLS when the record length varies widely from site to site and discharges are cross correlated. Their GLS approach permitted use of station records of different lengths. Non-overlapping flood records at the various sites prevents the calculation of actual cross correlations. This problem was overcome by assuming a constant cross correlation between the records of all sites within the region.

Six schemes that represent the range of approaches are described below.

Index Flood Method. For ungauged sites, the index flood is estimated using a relation between that flood and catchment and rainfall or regional variables derived from gauged sites in the same region. Typically, the relation takes the form

$$\overline{Q} = aB^bC^cD^d \tag{2·29}$$

where B, C and D are physiographic and climatic variables such as catchment area, channel slope and mean annual precipitation, and a, b, c, and d are parameters. Estimates of the parameters of the dimensionless regional frequency curve $\hat{\theta}_k^{(R)}$ (k = 1, ..., p) are obtained using one of the methods described in Section 2.6 and (2·7), and the estimate of X_T from the fitted curve . The estimate of Q_T is obtained with (2·9).

The index flood method [*Dalrymple*, 1960] was once the standard U.S. Geological Survey approach to RFFA. However, the U.S. Geological Survey abandoned the method after it was discovered that, in general, C_v varies approximately inversely with catchment area. This phenomenon is particularly noticeable when dealing with humid catchments of greatly differing size with larger catchments having flatter frequency curves [see, e.g., *Dawdy*, 1961;

Benson, 1962*a*; *Riggs*, 1973; *Smith*, 1992]. *Smith* [1992, Fig. 4] showed that C_v varied approximately with area for catchments with areas less than 26 km^2 and inversely with area for larger catchments in the central Appalachian region of Maryland and Virginia. Thus he suggested that peak flows in small catchments may behave differently from those in large catchments.

The index flood method has received considerable renewed attention since the introduction of the WAK distribution by *Houghton* [1978]. It is only valid for constant regional C_v and constant form of the parent distribution. *Gupta et al.* [1994] note that observed departures from the assumptions of the index flood method have often been attributed to a lack of regional homogeneity. They show that the departures are due to violations of the basic assumptions of the index flood method. The results of *Smith* [1992], *Wolff and Burges* [1994] and *Gupta et al.* [1994] introduce important considerations, critical to quantile estimation, that were not detectable by conventional statistical methods.

U.S. Geological Survey method. Floods of various AEPs are estimated at all gauged sites within a region. The discharge for each AEP is then related to catchment and rainfall or regional variables by a multiple regression model of the form

$$Q_T = aB^b C^c D^d \tag{2·30}$$

Regional homogeneity is assumed but there is no assumption of constant C_v within regions. This approach is called the Multiple Regression, Multiple Correlation or Quantile Regression method and is the principal method used by the U.S. Geological Survey [see, e.g., *Benson*, 1962*b*; *Cruff and Rantz*, 1965; *Riggs*, 1973]. Because of sample size considerations, this method can give a smaller estimated peak flood for a given AEP than for a smaller AEP [*Benson*, 1962*b*, p. B-52; *IEA*, 1987, p. 98]. However, hydrologic judgement can be used to make a slight adjustment to the flood frequency curve so that Q_T increases smoothly with T [*Benson*, 1962; *Kirby and Moss*, 1987].

Multiscaling method. *Gupta and Dawdy* [1994] and *Gupta et al.* [1994] apply the multiscaling theory of *Gupta and Waymire* [1990] to RFFA. *Smith* [1992] interpreted the different C_v versus area relationships for small and large catchments as grounds for not applying multiscaling theory. *Gupta et al.* [1994] have shown that *Smith's* [1992] results and the U.S. Geological Survey method are consistent with the theory. While multiscaling theory has had little application in RFFA, it merits continued development and testing.

The quantile regression equations for the multiscaling model can be expressed as

$$Q_T(A) = c(T)\, A^{\theta(T)} \tag{2·31}$$

where the coefficient $c(T)$ and the exponent $\theta(T)$ depend on the AEP of 1 in T. Equation (2·31) cannot conform with the index flood method unless $\theta(T)$ is independent of T. Unlike the U.S. Geological Survey method, catchment area is the only independent variable in (2·31). However, (2·31) is consistent with the Survey's experience in that the exponent has been observed to vary with T and that this variation is systematic.

The quantile equations can be written more explicitly as follows. Let A_l and A_u denote the drainage areas of two reference catchments such that

$$A_l \quad < \quad \min_i A_i \quad < \quad \max_i A_i \quad < \quad A_u \tag{2·32}$$

in which A_i denotes the catchment area of the ith site within the region of interest. Following the observations of *Smith* [1992] two ranges of a dimensionless parameter, defined as $\lambda = A/A_u < 1$ and $\lambda = A/A_l > 1$, are considered. The multiscaling representation of peak flows is different for each range. Let A_c denote the critical catchment area at which the nature of the variability of peak flows with area changes. The multiscaling model can be written as

$$\log Q_T(A) \quad = \quad (a_0 - \mu_0 \log A) \quad + \quad \left[b_0 - \sigma_0^\alpha \log A\right]^{1/\alpha} w'_T, \quad A_c < A < A_u \tag{2·33a}$$

and

$$\log Q_T(A) \quad = \quad (\mu_1 \log A - a_1) \quad + \quad \left[\sigma_1^\alpha \log A - b_1\right]^{1/\alpha} w'_T, \quad A_l < A < A_c \tag{2·33b}$$

where a_0, a_1, b_0, b_1, α, μ_0, μ_1, σ_0, and σ_1 are parameters to be estimated and w'_T is the $(1 - 1/T)$th quantile of $-W1$ where $W1$ is a random variable having a Levy-stable probability density with a 'characteristic exponent' of $0 < \alpha \leq 2$ [*Levy*, 1924; *Gupta and Waymire*, 1990]. For $\alpha = 2$, (2·33a) is known as the log normal scaling model, and for $\alpha = 1$ as the Cauchy model. Using the results of *Sivapalan et al.* [1990], *Gupta and Dawdy* [1994] and *Gupta et al.* [1994] present arguments indicating that parameters σ_0 and μ_0 can be interpreted in terms of mean rainfall and mean saturated soil hydraulic conductivity. Application of the multiscaling model to ungauged catchments will require further development of the linkage between the model parameters and catchment characteristics.

Gupta et al. [1994] applied the multiscaling model to 270 catchments in the central Appalachian region. This sample included the 104 catchments used by *Smith* [1992]. They examined five Levy distributions with different values for α and the skewness parameter, and four values for A_c. With the exception of α, the model parameters were estimated using OLS, a quasi-Newton optimisation scheme, and log-transformed empirical and model flood quantiles. *Gupta et al.* [1994] found while the presence of multiscaling in small catchments is much weaker than that in larger catchments for the central Appalachia data set, the moment predictions of the model give a good fit to the first four moments of all of the empirical data.

Reference ARI method. Here a regression model is developed for a reference ARI and average frequency factors for the region are applied to the estimates to determine floods of other ARIs [see, e.g., *Macqueen*, 1979; *McDermott and Pilgrim*, 1983].

Catchment response time method. *Potter and Faulkner* [1987] have proposed that the ratio of drainage area to time-to-peak (A/T_p) is a good indicator of flood quantiles. Using flow data from the quaternary geological 'driftless' area of Wisconsin, they compared the results of regressions of flood quantiles of various ARI on A/T_p, A alone, and A and annual precipitation P. They found that the standard errors of the regression estimates were markedly lower for the model that used A/T_p. Application of the method requires direct measurement of the river stage for one or more events at the site for which the quantiles are to be estimated. They argue that the cost may not be great given recent developments in hydrologic monitoring. However, this presupposes that the practitioner has the time to wait for one or more events to be recorded.

Rainfall-runoff modelling. Rainfall-runoff modelling offers a means of estimating flood quantiles at ungauged sites provided it is possible to obtain estimates of the model parameters and rainfall and evaporation data for the catchment of interest. One method of obtaining flood quantiles is to apply conventional flood frequency analysis to the streamflow series obtained from a continuous simulation rainfall-runoff model driven by historical rainfall and evaporation records. However, the record lengths for historical data are usually short and quantile estimates corresponding to low AEPs will involve considerable extrapolation of the probability distribution fitted to a synthesised annual flood series. Another method is to analyse a very long synthetic streamflow record obtained by driving the continuous rainfall-runoff model with a stochastic weather model [see *Bras et al.*, 1985]. This approach relies on the ability of the stochastic weather model to simulate rainfall occurrence and amounts during and immediately prior to extreme flood events.

Lichty and Karlinger [1990] explored the use of rainfall-runoff modelling as a means of deriving regionalised flood estimates. The rainfall-runoff model of *Dawdy et al.* [1972] was used together with long-term rainfall and pan evaporation records from 71 sites within the eastern United States to generate modelled annual flood series for 50 basins. A total of 3,550 (50 x 71) annual flood series were synthesised. The magnitudes of the modelled floods of AEP 1 in T (T = 2, 25, 100) were standardised by drainage area and were regressed against a reduced set of rainfall-runoff model parameters (sample size of 50) for each of the 71 rainfall sites. A log-transformed multiple linear regression model was used wherein the reduced set of parameters consisted of an infiltration factor and a hydrograph shape factor (lag time) which were expressed as functions of various model parameters. The values of the intercept of the regression models were regionalised using kriging. The accuracy of the regionalised flood quantiles was tested using observed annual flood series from 200 gauged catchments. The regionalised flood quantiles explained a large part of the variability in the at-site estimates with coefficients of determination ranging from 0·89 for the 1 in 2 year flood to 0·82 for the 1 in 100 year flood. The corresponding standard errors ranged from 45 to 57 percent. However, simple log-transformed regressions of the at-site floods on the regionalised floods revealed that the regionalised floods were biased estimators of observed floods since the regression constant and coefficient were significantly different from a zero intercept and unit slope, respectively.

Bradley and Potter [1992] proposed a ‘peak-to-volume’ approach for the estimation of flood quantiles. The method is based on the premise that runoff volume distributions conform more closely to well known parametric distributions than peak discharge distributions, particularly in the upper tail [see, e.g., *Bradley and Potter*, 1992, Figs 8 and 9]. Thus the extrapolation of a runoff volume distribution should be more reliable than an extrapolation of the peak discharge distribution. A GEV distribution is fitted to the three-day runoff volumes obtained from a continuous simulated streamflow series and a locally weighted regression model to the simulated flood peak discharge and runoff volume data. A flood is defined as an event where the peak discharge exceeded a specified threshold. The probability distribution of peak discharge is estimated by integrating the distribution of runoff volume with the conditional (truncated log normal) distribution of peak discharge on volume for different values of peak discharge. The annual peak discharge distribution is obtained from the distribution of peak discharge using the assumption that the threshold is sufficiently large enough that the peak discharges are independent and that floods occur according to a Poisson process. The application of the 'peak-to-volume' method to ungauged catchments is reliant on upon successful regionalisation of the rainfall-runoff model parameters and the conditional distribution of peak discharge on runoff volume, and the availability of historical or synthetic rainfall and evaporation data.

2.7.2 Derived flood frequency distributions

The derived flood frequency distribution approach offers a means of estimating flood quantiles at ungauged sites provided it is possible to estimate catchment response from catchment characteristics, climatic records and field observations. Thus it offers a means of deriving a flood frequency distribution from physical rather than purely statistical considerations. Derivation of the distribution by analytical means and the reduction of the need for model calibration requires the use of simplistic rainfall and catchment models. While these models may not be able to predict streamflow as well as complex models, it may be argued that the use of simple models is justified (and may be the only choice) for ungauged regions and that their predictions may be adequate for flood frequency analyses [*Moughamian et al.*, 1987].

Eagleson [1972] analytically derived the flood frequency distribution for a catchment idealised as an 'open-book' (or V-shaped plane) by assuming that rainfall intensity and duration are independent random variables with an exponential joint probability density function and by using kinematic wave overland flow dynamics. It was assumed also that the source area contributing to runoff is a narrow band symmetrical about the stream at the centre of the plane and that infiltration can be represented by a simple Horton model with constant infiltration capacity. *Eagleson* [1972] compared the mean annual floods from his derived flood frequency relations with direct runoff producing areas equal to $A/3$ and $A/2$ with those from observed annual flood series for 44 catchments in Connecticut. The two theoretical distributions bracketed the OLS regression line of observed log $\overline{Q}$ on log A. However, the catchment model contains parameters that are difficult to estimate without some measured streamflow data [*Moughamian et al.*, 1987].

Hebson and Wood [1982] and *Diaz-Granados et al.* [1984] have presented methods for deriving flood frequency distributions using *Eagleson's* [1972] rainfall model and catchment models based on the geomorphological unit hydrograph (GUH) concept [see, e.g., *Rodriguez-Iturbe and Valdes*, 1979; *Gupta et al.*, 1980; *Rodriguez-Iturbe et al.*, 1982*a*, *b*]. The GUH is an instantaneous unit hydrograph that is based on measurable channel network and catchment properties and is a simple function of measurable physical parameters. It is a linear rainfall-runoff model, and is interpreted as the probability density function of the travel time taken by a raindrop landing anywhere in the catchment to reach the catchment outlet.

Hebson and Wood [1982] used the same infiltration model as *Eagleson* [1972] and based their catchment model on the third-order GUH of *Rodriguez-Iturbe and Valdes* [1979]. Results from tests on two, third-order, Appalachian Mountain catchments showed that their procedure compared well with historical data and *Eagleson's* [1972] method.

Diaz-Granados et al. [1984] did not use the contributing area concept but assumed instead that the infiltration capacity varies with time according to the *Philip* [1957] model. Their catchment model was based on a later development of the GUH theory [*Rodriguez-Iturbe et al.*, 1982*a*]. In this model, the peak streamflow velocity parameter of the original GUH is replaced by an expression involving the intensity and duration of rainfall excess and the kinematic wave parameter for the stream of highest order as defined by *Rodriguez-Iturbe et al.* [1982*b*, Eq. 5]. The convolution integral for this approach is nonlinear in rainfall excess intensity. Diaz-Granados et al. tested their approach against the sample flood frequency distributions for arid and wet climates and achieved good and reasonable fits, respectively.

Moughamian et al. [1987] examined the performance of the *Hebson and Wood* [1982] and *Diaz-Granados et al.* [1984] procedures. They applied these methods to three different North American catchments. Each catchment had over forty years of streamflow data. The flood frequency distributions obtained from each procedure were compared with the sample distributions for each catchment. The derived distribution methods performed poorly in all three cases even when some of the model parameters were estimated from individual flood events. Many of these parameter estimates varied widely between events. The magnitude of the variability prompted *Moughamian et al.* [1987] to perform a sensitivity analysis wherein it was found that the cumulative effect of a number of relatively small errors in the rainfall and catchment models could be quite large. They concluded that derived methods need to be improved before they could be used in practice.

Suggested areas for additional research were the identification of the differences in the runoff generation mechanisms that are most influential for small through to large flood events and the development of probabilistic rainfall models that put greater emphasis on the nature of rare storms which are responsible for low AEP floods. *Moughamian et al.* also noted that it may be necessary to relate the catchment model assumptions and parameters more explicitly to storm intensity and duration.

Sivapalan et al. [1990] used the runoff generation model of *Sivapalan et al.* [1987] with a geomorphic instantaneous unit hydrograph catchment response model that incorporated the infiltration excess and saturation excess runoff generation mechanisms. They were able to examine the behaviour of runoff due to spatially variable rainfall and terrain. *Sivapalan et al.* [1990] found that: (1) in cases where flood generation is dominated by infiltration excess runoff, the shape of the flood frequency distribution can be specified by three dimensionless parameters (scaled mean rainfall intensity, scaled mean saturated hydraulic conductivity, and scaled catchment area); (2) variables such as average contributing area, initial catchment wetness and storm duration are constant across ARIs; and (3) the peaks for low ARI floods are dominated by saturation excess runoff with a transition to infiltration excess runoff for floods with high ARIs. While the model response is indicative of possible flood generation behaviour, it has yet to be tested against empirical flood data. *Gupta and Dawdy* [1994] and *Gupta et al.* [1994] demonstrate that the sensitivity of the flood frequency distribution to scaled catchment area plot presented by *Sivapalan et al.* [1990, Fig. 15] is consistent with multiscaling theory and not the index flood method. (Scaled catchment area was defined by Sivapalan et al. as $A^* = A/\lambda_p^2$ where λ_p denotes the rainfall correlation length scale.)

Cadavid et al. [1991] used *Eagleson's* [1972] rainfall model, *Philip's* [1957] infiltration equation and a kinematic overland flow model in an attempt to derive flood frequency distributions for small urban catchments. They applied their model to two catchments and compared the derived distributions with LP3 distributions fitted to the historical data. *Cadavid et al.* [1991] found that their approach gave a better fit to the low ARI floods than the high ARI floods. They concluded that Eagleson's exponential rainfall model may not be an accurate representation of the rainfall processes that cause floods and that the estimation of the rainfall model parameters appears to have a major effect on the success of the derived distribution approach.

Raines and Valdes [1993] modified the model of *Diaz-Granados et al.* [1984] by using the Soil Conservation Service curve number method rather than the Philip equation. They applied this model, the methods of *Hebson and Wood* [1982] and *Diaz-Granados et al.* [1984], and the *HEC-1* [1981] event-based simulation model to four catchments in Texas. *Raines and Valdes* [1993] noted that although the performance of their procedure was superior to previous approaches, none of the methods provided better results when compared with the LP3 distributions fitted to the historical data. They also concluded that the estimation of the rainfall model parameters was the major source of error.

2.8 Summary and Recommendations for Further Research

The general impression to be gained from most of the literature on the analysis of peak flood flow rates is that the best method available for regional flood frequency analysis (RFFA) is an index flood method based on the generalised extreme value (GEV) or Wakeby (WAK) distribution and *L*-moments. It avoids the inherent weakness in station year methods (bias due to neglecting inter-site dependence) and might have more utility than Bayesian methods. However, the degradation in performance of index flood methods for high $C_v(C_v)$ and $M(C_v)$, recent application of multiscaling theory to RFFA, the support that the theory lends to the empirical Quantile Regression method used by the U.S. Geological Survey, and the observation that C_v may vary with or approximately inversely with catchment area according to catchment scale, suggest that the index flood method should be viewed with some scepticism. Thus the assumptions of the index flood and multiscaling methods require immediate and thorough investigation using observed data from a variety of hydro-climatic regimes. Particular attention should be given to the applicability of both methods and the quantification of the benefits gained by using regional rather than at-site estimators of flood quantiles at gauged sites. Other potentially fruitful areas for continued investigation are the catchment response time method of *Potter and Faulkner* [1987] wherein the ratio of drainage area to time-to-peak is used as a indicator of flood quantiles and the combination of rainfall-runoff modelling and the catchment response time method as proposed by *Bradley and Potter* [1992].

A critical component of the index flood, multiscaling theory and catchment response time methods is the delineation of homogeneous hydrological regions. While much work has been done in this area, it is still not an issue that can be approached with any degree of confidence. Topics worthy of immediate attention are the identification of the key catchment characteristics that are responsible for similarities in hydrologic response as measured by statistics of annual flood peaks and volumes and the extent to which the region of influence (ROI) approach is superior to the use of regions based on geographically contiguous areas. In determining homogeneous regions, the entire flood hydrograph should be considered in that this may extract more information on the hydrologic response of catchments from the available data.

Although the current performance of the derived distribution approach is inadequate for immediate application, it may hold promise as a means of improving the physical basis of flood frequency analysis and scientific understanding of the flood process. Further work is needed with alternative rainfall, infiltration and catchment response models. Although the development of improved rainfall models and parameter estimation procedures are the most important tasks, work on the derived distribution approach should be given a low priority for the time being.

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3 REGIONALISATION OF RAINFALL-RUNOFF MODEL PARAMETERS

3.1 General Remarks

The regionalisation of rainfall-runoff model parameters allows the estimation of design flood hydrographs for sizing hydraulic structures on and the determination of water yield from ungauged catchments. It can also provide useful initial parameter estimates for calibrating models of gauged catchments.

There are three broad types of rainfall-runoff models:

- Discrete flood event models (such as the unit hydrograph and runoff routing methods) which represent a single runoff event occurring over a period ranging from less than one hour to several days. Many of these models contain conceptual elements with parameters that must be estimated by fitting computed hydrographs to observed hydrographs.

- Conceptual rainfall-runoff models (CRRMs) which simulate the complete land phase of the hydrologic cycle over an extended period of time. CRRMs consist of a series of submodels with each representing a particular hydrologic process. Each submodel usually includes a conceptual moisture storage element. CRRMs are frequently used for applications such as catchment yield analysis, the extension of streamflow records, infilling missing streamflow records, and studies of the effects of land use and climate change on catchment hydrology. Typical examples include the Stanford Watershed Model [*Crawford and Linsley*, 1966] and its derivative HSPF [*Johanson et al.*, 1984], the Sacramento Model [*Burnash et al.*, 1973], the SFB Model [*Boughton*, 1984], and the MODHYDROLOG Model [*Chiew and McMahon*, 1991]. These models have a lumped or at most quasi-distributed structure in that averaged or representative values of catchment characteristics must be utilised. This leads to an implicit averaging of the modelled hydrologic processes. By their very nature, these models have parameters that must be estimated by fitting computed hydrographs to observed hydrographs.

- Distributed parameter catchment models which use physically-based process equations to simulate the spatial variability of runoff due to spatial variations in land characteristics such as soil type and topography as well as rainfall. Typical examples include the SHE model [*Abbott et al.*, 1986*a*, *b*], the TOPOG model [e.g. *O'Loughlin et al.*, 1989], and the THALES model [*Grayson et al.*, 1992]. While these models have the potential to become a universally applicable tool, they come with the price of increased model complexity, data requirements and computing costs. As their application is usually limited to small catchment hydrology, they are more suited to scaling rather than regionalisation studies.

Regionalisation of rainfall-runoff model parameters has been attempted by regressing model parameter estimates obtained from gauged catchments on the physical characteristics of the catchments within an assumed hydrologically homogeneous region. The resulting relationships are empirical and cannot be expected to be universally applicable. In general their application should be restricted to the regions for which they have been derived. Successful regionalisation of the parameters of these models depends on:

- accurate estimation of model parameters for gauged catchments;
- the selection of catchment characteristics that affect catchment response to rainfall;
- the delineation of homogeneous regions;
- the degree to which the model parameters are correlated with catchment characteristics; and
- correct specification of the regression model for each region.

All of these depend on the availability of sufficient, good quality precipitation, potential evapotranspiration, streamflow, climatic and catchment characteristics data.

There is an abundant literature on the regionalisation of parameters of discrete flood event models [e.g., *Singh*, 1977; *Weeks and Stewart*, 1978; *Morris*, 1981; *Flavell et al.*, 1983; *Sobinoff et al.*, 1983; *James et al.*, 1987; *Karlinger et al.*, 1987; *Sabol*, 1988; *Yu*, 1989; *Sorman and Abdulrazzak*, 1990; *Dyer et al.*, 1993] and CRRMs [e.g. *Jarboe and Haan*, 1974; *Egbuniwe and Todd, 1976*; *Magette et al.*, 1976; *Hughes*, 1985; *Pirt and Bramley*, 1985; *Weeks and Ashkanasy*, 1985; *Srikanthan et al.*, 1989; *Lichty and Karlinger*, 1990]. The accuracy and precision of the predictions obtained from the resulting parameter-catchment characteristics relationships varies from good to very poor. This raises questions about the utility of the procedures used, the impacts of model and data error, and the extent of our knowledge of and capability to represent the link between catchment geomorphology and catchment response to rainfall. Thus it has been argued that the goal of relating model parameters to catchment characteristics has never been and may never be fully realised [*Boughton and Sefe*, 1982; *Larson et al.*, 1982; *Mein and McMahon*, 1982; *Weeks and Ashkanasy*, 1985].

Nevertheless the work to date suffers from a number of limitations. First, subjective trial and error fitting procedures have been used often to obtain model parameter estimates. This compromises the reproducibility of the estimates and can introduce bias [*James*, 1972; *James and Burges*, 1982; *Weeks and Ashkanasy*, 1985]. Second, the homogeneous regions identified in these studies were based on geographically contiguous areas which might not make the best use of information available on the hydrologic similarity of catchments (see Section 2·3). Third, a multiple linear regression model (MLRM) has been used in almost every case to describe the model parameter-catchment characteristics relationship with little evidence of an adequate investigation of the nature of its true functional form.

The selection of homogeneous regions is discussed in Section 2·3 and will not be repeated here. The material below will focus on parameter estimation issues and alternative regression models for model parameter-catchment characteristics relationships.

3.2 Estimation in Discrete Flood Event Models

Unit hydrographs for ungauged catchments are estimated using the synthetic unit hydrograph approach [see, e.g., *Synder*, 1938; *Clark*, 1945; *Nash*, 1960; *Cordery and Webb*, 1974; *U.S. Soil Conservation Service*, 1985]. It involves the estimation of a number of parameters that affect unit hydrograph shape from relationships between these parameters and catchment characteristics. Typical parameters include lag time, time to peak, unit hydrograph duration, time widths at 50 and 75% of peak flow, and runoff velocity. In most cases, estimates of these parameters are obtained by manual methods (exceptions include the works of *James et al.* [1987] and *Karlinger et al.* [1988]) and are regressed independently on a suite of catchment characteristics.

A common practice for the calibration of nonlinear runoff routing models is to use manual trail and error search to obtain estimates for the dominant parameter θ_k while fixing the remaining $p-1$ secondary parameters (θ_1, ..., θ_{k-1}, θ_{k+1}, ..., θ_p) to acceptable values. Estimates of θ_k are usually obtained by fitting observed and computed surface runoff hydrographs for individual storm events. These estimates are then combined (or pooled) to obtain a single estimate for the catchment at hand. The pooling procedure most frequently used is the calculation of the mean or median. A variation of this procedure is the use of parameter interaction diagrams by *Weeks* [1980] and *McMahon and Muller* [1985] to calibrate the RORB runoff routing model [*Laurenson and Mein*, 1990]. The diagrams are constructed by selecting a range of secondary parameter values and estimating the dominant parameter for each specified secondary parameter value. A plot of the resulting estimates produces a parameter interaction curve. This is repeated for all calibration events. The goal is to obtain a set of curves which intersect coincidentally at a unique parameter pair that provides a good fit for all events. This approach is rarely successful as the plots frequently take the form of sets of parallel rather than intersecting curves [see, e.g., *Bates et al.*, 1991].

Nonlinear regression techniques have been applied to nonlinear, discrete flood event models [*Singh*, 1977; *Williams and Yeh*, 1983; *Bates*, 1988; *Bates and Townley*, 1988*a*, *b*; *Bates*, 1990; *Kuczera*, 1990; *Bates et al.*, 1991; *Bates et al.*, 1993]. *Kuczera* [1990] and *Bates et al.* [1991, 1993] have presented evidence that estimates and the precision of the estimates of the dominant and secondary parameters of the RORB model vary markedly from storm to storm. The work of *Bates et al.* [1993] also suggests that secondary parameter estimates vary from catchment to catchment. While these works suggest that the use of the dominant parameter approach is flawed, current practices in the use of nonlinear regression theory are not beyond criticism. First, no account of any errors in the synchronisation of rainfall and runoff is taken during the estimation process. Such errors will have an adverse impact on the parameter estimates and hence on any model parameter-catchment characteristics relationship. Second, data transformations which favour the reproduction of small discharges at the expense of the hydrograph crest are often used to ensure that the least squares assumptions are not violated. While this weighting is broadly consistent with the precision of rating curves it is merely a statistical artefact. A better approach would be to use a weighting scheme based on quantitative information about the variation of the precision of the rating curve with increasing discharge. Such information can be obtained from gauging authorities.

Kuczera [1990] has devised a formal parametric pooling procedure for estimates of runoff routing model parameters which takes account of their varying precision between storm events. The procedure relies on the identification of a parameter transformation which allows the assumption of normality. The same transformation must be applicable to every flood event. *Bates et al.* [1991] examined the generality of these assumptions in the application of the RORB model to rainfall-runoff data sets from three Western Australian catchments. They found that Kuczera's distributional assumptions were untenable in every case and suggested that an alternative pooling method needed to be found.

3.3 Estimation in Conceptual Rainfall-Runoff Models

The application of automatic parameter estimation procedures to CRRMs has received considerable attention over the last two decades [e.g. *Johnston and Pilgrim*, 1976; *Sittner, 1976; Sooroshian and Dracup*, 1980; *Boughton and Sefe*, 1982; *Kuczera*, 1983; *Alley*, 1984; *Gan and Burges*, 1990*a*, *b*; *Chiew et al.*, 1993; *Sorooshian et al.*, 1993; *Bates* 1994; *Bates et al.*, 1994]. Many of these studies have reported difficulties in obtaining global and feasible parameter estimates. These difficulties have been attributed to: parameter interdependence; model and data error, nonconvexity of the response surface defined by the objective function; inconsistencies due to the spatial averaging of catchment properties and input data; discontinuous derivatives; and the existence of multiple optima.

Catchment dynamics, scale and climate dictate the minimum time step necessary to represent all significant hydrologic processes. There are many situations where available data do not conform with the minimum time step indicated by the dynamics. For example, in most Australian applications, CRRMs are driven by daily rainfall totals and estimates of daily potential evapotranspiration. This is largely due to the paucity of rainfall data for smaller time scales. Assessments of model fit are usually made by comparison of observed and computed monthly runoff totals [see, e.g., *Johnston and Pilgrim*, 1976; *Boughton and Sefe*, 1982; *Kuczera*, 1983; *Nathan and McMahon*, 1990; *Chiew et al.*, 1993; *Bates*, 1994; *Bates et al.*, 1994]. In studies where automated parameter estimation methods have been used, the most general objective function used can be defined by

$$S(\theta) \;=\; \min_{\theta} \sum_{t=k}^{n} z_t^2 \tag{3·1}$$

where

$$z_t \;=\; [(q_t^{\lambda} \;-\; Q_t^{\lambda}) \;-\; \phi(q_{t-1}^{\lambda} \;-\; Q_{t-1}^{\lambda})] \,/\, \lambda, \qquad \lambda \neq 0 \tag{3·2a}$$

or

$$z_t \;=\; [(\log q_t \;-\; \log Q_t) \;-\; \phi(\log q_{t-1} \;-\; \log Q_{t-1})], \qquad \lambda = 0 \tag{3·2b}$$

is the disturbance for the *t*th month in the calibration period, $\theta = (\theta_1, \ldots, \theta_p)^{\mathrm{T}}$, n is the number of months in the calibration period, q_t is the observed runoff for the *t*th month, Q_t is the computed runoff for the *t*th month, λ is a transformation constant, ϕ is the parameter for a first-order autoregressive process, $k = 1$ for $\phi = 0$, and $k = 2$ for $\phi \neq 0$. The use of $\lambda = 1$ favours reproduction of large flows while the reproduction of small flows is favoured when $\lambda < 1$.

A variety of local search algorithms have been used to calibrate CRRMs. They include the use of: steepest descent by *Boughton and Sefe* [1982]; direct search method of *Rosenbrock*

[1960] by *Alley* [1994]; the simplex method of *Nelder and Mead* [1965] by *Johnston and Pilgrim* [1976], *Sorooshian and Dracup* [1980] and *Weeks and Ashkanasy* [1985]; the Gauss-Marquardt algorithm [see *Bard*, 1974] by *Kuczera* [1983]; and the pattern search method of *Hooke and Jeeves* [1961] by *Hendrickson et al.* [1988] and *Chiew et al.* [1993]. With these methods, several optimisation runs with different initial parameter estimates are usually performed and the best result is retained as the candidate for the global optimum θ^*. Such an approach may be described as a deterministic global optimisation procedure. Although this multistart approach is more efficient than a pure random search, it will cause each local minimum to be found several times.

Stochastic global optimisation methods are now a viable alternative to deterministic local search procedures. In these methods the minimisation process depends partly on probabilistic events. Under mild conditions on $S(\theta)$, stochastic methods guarantee asymptotic convergence to θ^* as the number of sample points increases. Successful application of these methods to practical problems still requires a very large number of function evaluations (CRRM runs). Nevertheless, they are time efficient because of the computing speeds now available and often produce better results than deterministic methods [*Corana et al.*, 1987; *Eglese*, 1990]. The works of *Duan et al.* [1992], *Sorooshian et al.* [1993] and *Bates* [1994] have confirmed these findings for CRRMs.

Wang [1991] described and applied a genetic algorithm to the calibration of the Xinanjiang Model developed by *Zhao et al.*, [1980]. The method searches among a population of points and works with a binary coding of the parameter set rather than parameter values. An initial set of points is chosen at random and $S(\theta)$ values computed for each point. A new set of points is generated using a partially random selection that is concentrated in the vicinity of those points which have low $S(\theta)$ values. The new set of points forms the basis for the next iteration of the search. A record is kept of the best point found during the estimation process. The process is continued until a prespecified number of function evaluations is reached. The resulting estimates can be further tuned by applying a conventional local search method. The genetic algorithm is analogous to the concept of the survival of the fittest in the theory of natural selection.

Duan et al. [1992, 1994] and *Sorooshian et al.* [1993] described a shuffled complex evolution algorithm (SCE-UA) and applied it to the Sacramento Model. The SCE-UA method involves the initial selection points distributed randomly throughout the feasible parameter space. These points are partitioned into several 'complexes' with each complex consisting of $2p + 1$ points. Each complex is allowed to search the parameter space (or 'evolve') independently using a modified simplex method. After a prescribed number of steps, the complexes are 'shuffled' and new complexes are formed using the information obtained from the independent searches. The evolution and shuffling procedures are repeated until the prescribed stopping criteria are met.

Bates [1994] described and applied a three-phase simulated annealing algorithm (SA-SX) to the calibration of the SFB Model [*Boughton*, 1984]. In the first (or *presampling*) phase, $(p+1)^2$ parameter vectors are randomly generated and sorted according to their $S(\theta)$'s. The parameter vectors that produce the $(p+1)$th smallest $S(\theta)$ values form the initial Nelder-Mead simplex. In the second (or *global*) phase, simulated annealing (SA) is used until the algorithm is close to converging to a minimum. SA was proposed by *Kirkpatrick et al.* [1983] as a method for minimising multivariate functions. It is an iterative stochastic method that has the ability to migrate through a sequence of local minima in search of the global solution. This is achieved by accepting steps corresponding to a decrease in $S(\theta)$ as well as steps corresponding to an increase in $S(\theta)$. The latter is done in a limited way by means of a stochastic acceptance criterion. This makes it possible to escape from a local minimum and to explore the parameter space entirely. In the course of the optimisation process, the probability of accepting moves which increase $S(\theta)$ decreases slowly to zero. SA is especially attractive when $S(\theta)$ is not smooth or continuous in its domain as the method does not require the calculation of derivatives. Rather than waste time attempting uphill steps that will always be rejected, the annealing process is stopped and in the third (or *local*) phase the simplex (SX) method is used to locate a candidate global optimum.

Although the results of research on the application of stochastic optimisation methods to CRRMs is encouraging, the amount of testing done so far is small. Many of these methods contain algorithmic parameters which can have a marked effect on performance. Values for these parameters have to be decided a priori and there is little guidance in the literature on parameter selection. The development of guidelines for algorithmic parameter selection, and a comprehensive comparison of the performances of the genetic, SCE-UA and SA-SX methods, would be useful steps in improving parameter estimation in CRRMs.

3.4 Regression Models for Parameter-Catchment Characteristics Relationships

In the absence of any formal physically-based scheme for the regionalisation of rainfall-runoff model parameters, resort has been made to regression modelling. Consider the regionalisation problem consisting of a p-parameter rainfall-runoff model, a homogeneous region consisting of n catchments, and q (possibly log-transformed) catchment characteristics. The relationship between the ith parameter and the catchment characteristics is almost universally represented by the multiple linear regression equation:

$$\theta_i = \mathbf{X}\beta + \varepsilon \tag{3·3}$$

where θ_i is the $n \times 1$ vector of θ_i estimates, $\mathbf{X}$ is the $n \times (q+1)$ matrix of observations on the catchment characteristics, β is the $(q+1) \times 1$ vector of unknown regression parameters, and ε is the $n \times 1$ vector of error terms which are assumed to be independent and identically distributed normal random variables with mean zero and unknown variance σ^2.

The use of (3·3) is predicated on two major assumptions: (1) the correlations between θ_i and the remaining $(p-1)$ parameters are negligible; and (2) the functional form of (3·3) is correct. For discrete event models, it is often assumed that: (1) the values of any secondary parameters are constant across catchments within the homogeneous region; and (2) the precision of the θ_i estimates is constant across events and hence that simple averaging of the estimates for individual events is an appropriate pooling procedure for each catchment.

The functional form of (3·3) has no theoretical support; its prevalence in the literature may be due primarily to the general availability of computer software for fitting MLRMs to data. Although regression diagnostics has now reached an advanced state [see e.g., *Belsley et al.*, 1980; *Bates and Sumner*, 1991], there have until recently been few useful tools for identifying nonlinear relationships in multivariate data.

Generalised additive models (GAMs) offer a flexible way of identifying nonlinearities by allowing the data to suggest their form through the application of nonparametric scatterplot smoothers [*Hastie and Tibshirani*, 1990]. An additive regression model for the ith model parameter has the general form

$$\theta_i(\mathbf{X}) = \beta_0 + f_1(\mathbf{x}_1) + \ldots + f_q(\mathbf{x}_q) \tag{3·4}$$

where each of the $\mathbf{x}_j$ ($j = 1, \ldots, q$) are predictors (catchment characteristics), the f_j are smooth functions of the predictors (usually involving parameters) to be estimated, and β_0 is the intercept term. The terms in the righthand side of (3·4) may be parametric compound or even multivariate nonparametric variables. Thus they can be used in a diagnostic mode as a tool for suggesting parametric transformations (such as logarithm, polynomial and sinusoid) or alternative forms for the terms in the model. Once appropriate transformations have been discovered, subsequent fitting and testing can be based on these parametric transformations.

There is a link between GAMs and the *Andrews'* [1972] curves used by *Dyer et al.* [1993]. An Andrews curve is defined by

$$f(\mathbf{x}) = \frac{x_1}{\sqrt{2}} + x_2 \sin(t) + x_3 \cos(t) + x_4 \sin(2t) + x_5 \cos(2t) + \ldots \tag{3·5}$$

where $x_1, x_2, \ldots$ are the variables used to characterise a catchment and $-\pi < t < \pi$. Equation (3·5) is similar in form to (3·4). However, (3·5) characterises the q-dimensional space defined by the catchment variables for a single catchment as a two-dimensional curve whereas (3·4) expresses the relationship between the ith model parameter and values of the catchment variables for all of the catchments of interest.

Multivariate linear and multivariate nonlinear regression [*Theil*, 1971; *Krzanowski*, 1988; *Bates and Watts*, 1988] provide a means of deriving parametric parameter-catchment characteristics relationships when estimates for more than one model parameter (response) are available and the model parameter estimates are found to be highly correlated with each other. Here information from all the model parameters can be combined to provide more precise regression parameters and to determine more realistic function forms for model parameter-catchment characteristics relationships. The multivariate linear regression model can be written in the form

$$\Theta = \mathbf{XB} + \mathbf{E} \tag{3·6}$$

where Θ is the $n \times p$ matrix whose ith column is θ_i, $\mathbf{B}$ is the $(q+1) \times p$ matrix of unknown regression parameters and $\mathbf{E}$ is the $n \times p$ matrix of error terms whose rows are independent observations from a multivariate normal distribution with mean zero and dispersion Σ. The multivariate nonlinear regression model may be written as

$$\Theta = f(\mathbf{X}, \mathbf{B}) + \mathbf{E} \tag{3·7}$$

where $f(\mathbf{X}, \mathbf{B})$ is the regression model response function. GAMs can assist in the identification of the functional form of $f(\mathbf{X}, \mathbf{B})$.

If no parameter-catchment characteristics relationships can be found, geostatistics may provide a means of deriving values for one or more of the model parameters on the basis of geographical location alone.

3.5 Estimating Design Floods and Water Yield From Ungauged Catchments

Mein and Brown [1982] note that most ungauged catchments do not have continuous and concurrent rainfall and evaporation data and hence that the application of CRRMs to these catchments leads to the requirement of a synthetic input. They suggested that the generation of synthetic daily input data was not a matter of routine. A decade later, the situation remains largely unchanged.

A few studies have considered the application of stochastic daily precipitation models to Australian data at the daily time scale [e.g *Wickramasuriya et al.*, 1982; *Srikanthan and McMahon*, 1983*a*, *b*; *Srikanthan*, 1985; *Guenni et al.*, 1990; *McCaskill*, 1992; *Bates et al.*, 1994; *Chapman*, 1994]. Most of these works have examined multi-state, first order, discrete Markov models of daily rainfall occurrence. Exceptions include the works of *Wickramasuriya et al.* [1982] who considered the use of discrete distributions, *Guenni* [1990] who used a modified Bartlett-Lewis rectangular pulses Poisson model in which the pulse height was gamma rather than exponentially distributed, and *Chapman* [1994] who considered a suite of higher order Markov models and alternating renewal process models.

Nevertheless, many other point rainfall occurrence models exist including variants of the Bartlett-Lewis model [e.g. *Onof and Wheater*, 1993], *Hutchinson's* [1990] three-state continuous Markov model, the Markov renewal model of *Foufoula-Georgiou and Lettenmaier* [1987], and Neyman-Scott rectangular pulse models [e.g. *Entekhabi et al.*, 1989; *Cowpertwait*, 1991]. These models have not been applied to Australian rainfall data. The Barlett-Lewis and Neyman-Scott models hold particular promise in that they may be applicable across a range of time scales (e.g. hourly to daily) whereas Markov chain models are highly parameterised for fine time scales and do not, in general, adequately represent the clustering dependencies present in observed daily rainfall occurrences [*Pattison*, 1965; *Foufoula-Georgiou and Lettenmaier*, 1987]. Recently, emphasis has shifted towards the modelling of precipitation in time and space over mesoscale catchments [e.g., *Zucchini and Guttorp*, 1991; *Bardossy and Plate*, 1992; *Hughes, et al.*, 1993].

Srikanthan [1985], *Guenni et al.* [1990], *McCaskill* [1992] and *Bates et al.* [1994] have investigated stochastic weather models for simulating daily rainfall, minimum and maximum temperature, and solar radiation. *Srikanthan* also considered pan evaporation. *McCaskill* [1992] and *Bates et al.* [1994] applied the WGEN generator of *Richardson and Wright* [1984] to Australian data sets and found its performance to be deficient. The work of *Guenni et al.* [1990] was limited to three Australian data sets but their generator appeared to offer reasonable performance.

Regardless of the approach chosen, the most important requirement will be a method for estimating appropriate stochastic weather model parameters for sites or catchments at which there are no climatic records. This is a topic that has received very little attention in the literature.

3.6 Summary and Recommendations for Further Research

The above review has highlighted the need for further research in almost all aspects of the problem of regionalising rainfall-runoff model parameters. It was found that much remains to be done with respect to parameter estimation and model parameter-catchment characteristics relationships. In particular, future research efforts should be concentrated on:

- improved objective function setting for parameter estimation in discrete flood event models;
- the development of new pooling procedures for combining parameter estimates obtained from individual storms;
- an investigation of the utility and performance of stochastic optimisation algorithms for parameter estimation in conceptual rainfall-runoff models (CRRMs); and
- a more thorough exploration of the functional form of model parameter-catchment characteristics relationships.

The problem of delineating homogeneous hydrological regions has received little attention in this Section. Nevertheless, it merits serious attention; the identification of homogeneous regions will have a direct bearing on the usefulness of any regionalisation of rainfall-runoff model parameters.

The problem of estimating water yield from ungauged catchments will require the development of improved stochastic weather models for generating synthetic input data for CRRMs. This is a topic for future research effort.

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4. LOW FLOW ESTIMATION

4.1 General Remarks

Abnormally low streamflow is the most notable characteristic of a hydrologic drought, defined by *Dracup et al.* [1980] as a period of streamflow deficiency. This section of the report examines procedures for the calculation of low flow statistics from observed data and their estimation at ungauged sites. There is a plethora of low flow statistics which quantify different aspects of low flow regimes and have different applications. These include [*Nathan and McMahon*, 1990*a*; *Gustard et al.*, 1992; *Nathan and Weinmann*, 1993]:

- simple, descriptive statistics of daily, monthly and annual flows (e.g, minimum, maximum, mean, standard deviation, standard errors of the mean and standard deviation, coefficients of variation and skewness, and lag-one serial correlation);

- flow regime statistics (such as: a baseflow index (*BFI*) related to the ratio of baseflow volume to total streamflow volume; *Colwell's* (1974) indices of predictability, constancy and contingency; and the percentage of time that the catchment ceases to flow);

- flow duration curves for daily, monthly and annual flows;

- flow frequency curves (e.g., annual minima for durations ranging from 1 day to six months);

- low flow spells (duration below a given threshold; frequency with which flow remains continuously below a given threshold for a given duration);

- deficiency volumes of low flow spells (below a given threshold; frequency of requirement for a given volume of water to maintain a given threshold flow);

- streamflow recession constant;

- storage yield (storage required to meet a specified draft at a given level of reliability);

- time to accumulate a given runoff volume with a given frequency of occurrence; and

- conceptual rainfall-runoff model parameters for the conversion of rainfall into runoff volumes.

The regionalisation of rainfall-runoff model parameters is discussed in Section 3 and will not be repeated here. Collectively, the remaining measures incorporate information on: the time of occurrence; duration that a threshold flow is exceeded or not exceeded; magnitude; central tendency; variability; persistence; and the frequency of specified events. A threshold is usually defined as some fraction of the mean daily, monthly or annual flow. In many cases, dimensional low flow statistics are standardised by the mean flow to enable comparison of these statistics between catchments by removing the scale of the hydrologic response. The information obtained from these measures is useful in reservoir design and regulation, licensing of stream abstractions, groundwater and environmental studies, water quality management, and the maintenance of sufficient flows for hydroelectric power generation, irrigation, fisheries, recreation, tourism, and navigation [*Gustard et al.*, 1992; *Nathan and Weinmann*, 1993; *Vogel and Fennessey*, 1994].

A common thread with the regionalisation of low and high flow statistics and rainfall-runoff parameters is the identification of homogenous regions. This issue is discussed in Section 2·3 and will not be considered further.

4.2 Calculation of Flow Statistics for Gauged Catchments

4.2.1 Simple descriptive statistics

A number of simple descriptive statistics have been used with a view to regionalisation. These include:

- mean annual discharge [*Lull and Sopper*, 1966; *Mustonen*, 1967; *Taylor*, 1967; *Hawley and McCuen*, 1982; *Horn*, 1988; *Nathan and McMahon*, 1990*a*];
- mean seasonal runoff and daily mean discharge [*Lull and Sopper*, 1966];
- minimum annual mean monthly flow [*Wright*, 1974];
- specific instantaneous discharge at low flow [*Whitehouse et al.*, 1983]; and
- standard deviation, skew coefficient and first-order serial correlation coefficient of annual streamflows [*Horn*, 1988; *Nathan and McMahon*, 1990*a*].

4.2.2 Baseflow and recession analysis

There is a general consensus that it is important to index the hydrogeology of catchments if low flows are to be predicted successfully at an ungauged site [*Institute of Hydrology*, 1980; *Gustard et al.*, 1992; *Nathan and Weinmann*, 1993]. The *BFI* measures the proportion of streamflow derived from stored sources. The use of a *BFI* entails the separation of baseflow from the total streamflow hydrograph on a continuous basis. Separation techniques that have been suggested include: empirical smoothing and separation rules [*Institute of Hydrology*, 1980; *Gustard et al.*, 1992]; simple scaling techniques [*Boughton*, 1988]; and recursive digital filters [*Lyne and Hollick*, 1979; *Nathan and McMahon*, 1990*a*, *b*]. *Nathan and McMahon* [1990*b*] found that the digital filter was superior to simple smoothing and separation in that it is better suited to the low baseflow conditions experienced within Australia, is less variable, and is more strongly correlated with other low flow indicators. In regionalisation procedures, the *BFI* has been used for cases involving stations with short records [e.g., *Gustard et al.*, 1992] or ungauged sites [e.g., *Nathan and McMahon* [1990*a*]. In the latter case, the *BFI* is estimated from readily available catchment characteristics data, and the estimate is used in a regional estimation equation together with other variables to compute the desired low flow statistic.

Recession analysis examines the rate at which water is released from stored sources. It provides a means of forecasting low flows during extended dry periods and relating low flows to hydrogeology and geomorphology [*Weyer and Karrenburg*, 1970; *Grant*, 1971; *McMahon and Mein*, 1986]. Semi-logarithmic plots of hydrograph recessions can be frequently approximated by several straight line segments. Each straight line can defined by

$$q_t = q_0 K_r^t \tag{4·1}$$

where q_t is the discharge at time t, q_0 is the initial discharge, and K_r is the recession constant dependent on the units of t. In low flow studies, interest is focused on the segments with the highest K_r values obtained during prolonged dry periods.

4.2.3 Flow duration analysis

A flow duration curve depicts the relationship between any given discharge and the percentage of time during which that discharge is equalled or exceeded during the period of record without regard to the sequence of flow occurrence. The flow duration curve is a cumulative frequency distribution determined by integrating the frequency distribution of historical flows [*McMahon and Mein*, 1986; *Vogel and Fennessey*, 1994]. Low flow indices derived from flow duration curves include:

- parameters of exponential and third order polynomial regression models fitted to flow duration curves [*Quimpo et al.*, 1983; *Mimikou and Kaemaki*, 1985];
- 95 percentiles for ten day flows [*Institute of Hydrology*, 1980] and one day flows [*Gustard et al.*, 1992] denoted by $Q_{95}(10)$ and $Q_{95}(1)$, respectively;
- Q_2, Q_5, Q_{30}, Q_{95}, and the mean. These statistics define points on a log-normal probability plot through which a smooth curve can be drawn [*Dingman*, 1978]; and
- Q_{10} and Q_{90} for perennial streams, or Q_{10} and the percentile at which a specified small fraction of the mean annual flow is equalled or exceeded (Q_m) for intermittent streams. A straight line joining the Q_{10} and Q_{90} or Q_{10} and Q_m statistics on a log-normal probability plot gives an approximation to the flow duration curve for an ungauged catchment [*Nathan and McMahon*, 1990*a*].

4.2.4 Low flow frequency

Low flow frequency curves can be used to determine the exceedance probability of a flow event of specified magnitude. The most commonly used probability distributions for low flow frequency analysis are the normal, log-normal, gamma, LP3, and Weibull [*Chang and Boyer*, 1977; *Nathan and McMahon*, 1990*a*; *Vogel and Kroll*, 1990]. *Nathan and McMahon* [1990*c*] carried out a detailed comparison of three estimation methods (moments, maximum likelihood and PWM) used for fitting the Weibull distribution to annual minima series for 134 Australian gauging stations. They concluded that PWM was best. *Vogel and Kroll*

[1990] found that the two-parameter log-normal distribution fitted annual minimum d-day low flow data for 23 stations in Massachusetts where $d = 3, 7, 14$, and 30. Flow indices used to characterise low flow frequency curves include:

- annual minimum 7-day flow with an ARI of 10 years [*Chang and Boyer*, 1977];
- 7-day mean annual minimum flow [*Gustard et al.*, 1992]; and
- proportion of zero flows or the 50 year ARI low flow event, the 2 year ARI low flow event, and the shape parameter of Weibull distribution [*Nathan and McMahon*, 1990*a*];

4.2.5 Spell duration and deficiency volumes

A frequency analysis of low flow spells consists of finding the longest spell duration and/or largest deficit volume where streamflow stays below a specified threshold for each year of record. A probability distribution is then fitted to the resulting annual maxima low flow duration series. The *Institute of Hydrology* [1980] and *Nathan and McMahon* [1990*a*] have found the maxima to be log-normally distributed. Thus *Nathan and McMahon* [1990*a*] used the 2 year and 50 year ARI events to characterise the entire frequency curve.

Paulson et al. [1985] considered three indices of drought: (1) drought severity, defined as the cumulative deficit volume below average annual streamflow; (2) drought magnitude, defined as the average deficit below average annual streamflow; and (3) drought duration, defined as the number of years where flow was continuously below average annual streamflow. Drought severities and magnitudes for 10%, 50% and 90% exceedance probability levels were obtained graphically using the Weibull plotting position. Drought duration was defined in terms of: termination probabilities for the n-year drought where $n = 1, 2, \ldots, 5$; mean termination probability, and mean drought duration. (Termination probability is defined by dividing the number of n-year droughts by the number of droughts lasting n years or longer.)

4.3 Low Flow Estimation for Ungauged Catchments

The estimation of low flow statistics at ungauged sites usually relies on the classification of catchments into physiographic types and the transfer of flow data between catchments in the same homogeneous region. Thus the problem has much in common with regionalisation techniques in other fields. *Nathan and McMahon* [1990*a*] note that are three possible approaches: (1) if rainfall records are available, undertake short term stream gauging to enable the calibration of a rainfall-runoff model, and extend (hindcast) the streamflow record; (2) directly transfer results from a similar, adjacent gauged catchment; and (3) use regional prediction equations. A fourth approach is to use contour maps of low flow indices [e.g. *Quimpo et al.*, 1983; *Horn*, 1988]. The second approach is contingent upon the user's ability to define an appropriate measure of 'similarity'.

Nathan and McMahon [1990*a*] state that the costs involved in short term stream gauging are rarely justified for small catchments and that it is rare to find cases where the direct transfer of low flow characteristics from one catchment to another can be made with a reasonable degree of confidence. *Hawley and McCuen* [1982] note that mapping is only appropriate for indices that are highly correlated with latitude and longitude (or a similar spatial coordinate system), and that regional estimation equations are preferable when this correlation is weak. Thus the regionalisation problem is usually reduced to the development of regression models to estimate low flow statistics at ungauged sites from readily available data on geomorphic, geologic, climatic, topographic, and land use characteristics [e.g.. *Lull and Sopper*, 1966; *Mustonen*, 1967; *Taylor*, 1967; *Wright*, 1974; *Chang and Boyer*, 1977; *Dingman*, 1978; *Quimpo et al.*, 1983; *Whitehouse et al.*, 1983; *Mimikou and Kaemaki*, 1985; *Paulson et al.*, 1985; *Horn*, 1988; *Curran*, 1990; *Nathan and McMahon*, 1990*a*; *Vogel and Kroll*, 1990]. Many of these studies have met with only limited success.

Most regional estimation equations conform to the MLRM defined by (3·3). *Nathan and McMahon* [1990*a*, p. 84] give a comprehensive summary of the catchment characteristics used. As noted in Section 3·4, there is scope to undertake more rigorous investigations of the functional form of these equations.

4.4 Summary and Recommendations for Further Research

Perhaps the most pressing problems associated with low flow estimation for ungauged catchments are the need to delineate homogeneous hydrological regions and the functional form of low flow statistics-catchment characteristics relationships. *Nathan and McMahon* [1990*a*] note that there is a need to conduct an extensive study of the low flow hydrology of many areas of Australia.

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5. CONCLUSIONS

This review has examined the regionalisation problem with respect to flood frequency, rainfall-runoff model parameters and low estimation. Emphasis has been placed on the need to obtain information for ungauged catchments since this is the problem of most interest to practitioners.

The following have been identified as high priority areas requiring further research:

- the delineation of homogeneous hydrological regions. This work should focus on the identification of the climatic and catchment characteristics that are responsible for similarities in the hydrologic response of catchments;

- exploration of the functional form of the relationships between flood and low flow quantiles, index flood, and rainfall-runoff parameters and catchment characteristics. This work should concentrate on whether the multiple linear regression models used in most regionalisation studies are adequate or whetheralternative forms offer a better description of the relationships, and on the utility of multivariate as opposed to single response regression models;

- investigation of the coupled index flood and *L*-moments approach, multiscaling theory, and the catchment response time and 'peak-to-volume' methods. This work should focus on empirical tests of the validity of the index flood and multiscaling theory assumptions, and the utility of the catchment response time method relative to the index flood and multiscaling theory approaches;

- the development and testing of improved parameter estimation techniques for discrete flood event models;

- investigation of the utility of optimisation algorithms for estimating the parameters of conceptual rainfall-runoff models and the development of guidelines for their efficient operation;

The following have been identified as important areas for further research but have lower priority:

- development and testing of stochastic rainfall models, infiltration and catchment response models for deriving flood frequency distributions by analytical means; and

- development and testing of stochastic weather models for sites and catchments with no climatic records. Provided other work on the regionalisation of rainfall-runoff models succeeds, this work will allow the estimation of water yield from ungauged catchments.

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APPENDIX A – NOTATION

A.1 Acronyms and Abbreviations

AEP	annual exceedance probability
ARI	average recurrence interval
CRRM	conceptual rainfall-runoff model
EB	empirical Bayes (theory/technique)
EV1, EV2, EV3	extreme value (distribution) types 1, 2 and 3
GAM	generalised additive model
GEV	generalised extreme value (distribution)
GLS	generalised least squares
GUH	geomorphological unit hydrograph
IACWD	Interagency Advisory Committee on Water Data
IEA	Institution of Engineers, Australia
LEB	linear empirical Bayes (theory/technique)
LP3	log Pearson Type III (distribution)
MLRM	multiple linear regression model
NERC	Natural Environment Research Council
OLS	ordinary least squares
PN	power normal (distribution)
PWM	probability weighted moments
RFFA	regional flood frequency analysis
ROI	region of influence (approach)
TCEV	two-component extreme value (distribution)
WAK	Wakeby (distribution)
WLS	weighted least squares

A.2 English Letters

A	catchment (drainage) area
BFI	baseflow index
C_v	coefficient of variation
$E[\cdot]$	expectation operator
g	skew coefficient
L	total period od record at M gauged sites
L CV	L-moment coefficient of variation (also denoted by τ)
M	number of gauged sites
$M(C_v)$	mean or median C_v
MSE	mean-square error
N_j	sample size for site j
Q	magnitude of the largest flood discharge which occurs in a year at a given site, Sec. 2
	monthly runoff, Sec. 3
Q_T	flood quantile of AEP 1 in T years or ARI of T years
$\overline{Q}$	mean of the annual flood maxima series at a given site
u	L-moment ratio vector
X	standardised flood discharge, Eq. (2·5)
X_T	regional growth factor of AEP 1 in T or ARI of T years
$\mathbf{X}$	matrix of observations on catchment characteristics, Sec. 3
Z	$\log Q$

A.3 Greek Letters

θ_k	kth distribution or model parameter

λ	Box-Cox transformation parameter, Eq. (2·15) and Sec. 3
λ_r	rth L-moment
τ	L-moment coefficient of variation (also denoted by L CV)
τ_3, τ_4	L skewness and L kurtosis, respectively

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